

NEWCASTLE UNIVERSITY

**Space Time Geography of Malaria and the Environmental Risks to Households,
Lagos State, Nigeria**

A Thesis Submitted in partial fulfillment of the requirements for full award of Doctor of
Philosophy, School of Geography, Politics and Sociology

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Abstract

The research employs the theoretical lens of human ecology of disease to examine the ecology of malaria in Lagos state, Nigeria. As a first step I examine the spatial and temporal trends in clinical malaria infection using a density-based algorithm to identify two locations (Ikeja and Kosofe LGAs) with one of the highest malaria infection rates and ecologically diverse terrain. They form the focus of this research.

I gather data and derive measures on 26 theoretically relevant environment and socio-cultural risk variables in a cross-section of 208 households using mixed methods that comprise semi-structured interviews, a questionnaire, environmental observations, GIS and remote sensing data and GPS mapping. Through these efforts, I build a household spatial database. I assess the contributory influences of the risk variables through the development and assessment of ten ecologically relevant candidate models of urban malaria using statistical and GIS analysis. I also engage with the everyday lives of the households and qualify the quantitative relationships.

Findings reveal that the most parsimonious candidate model is grounded on the human ecology of disease principle. While many of the variables are not statistically significant, some, such as travel history, animal presence and household size, are of public health importance. One important finding emerges. The risk variable “working at night without mosquito protection”, though it does not appear in this model, seems to be important across other models. I examine it further and note that its risk within households is higher than those associated with residential locations. In fact, households inhabit low-risk locations and have low vulnerability risk rates. This suggests that in urban areas, infection likely occurs outside homes and mostly from places of work or social gathering, and coincides with older household members rather than vulnerable children. This research suggests further insights for urban-like occupations and behaviours.

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*My mum Elizabeth who made me a
coat of many colours, and my
children Tobenna and Oluchi who
became part of it*

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List of Abbreviations

AIC: Akaike Information Criteria

ACD: Active Case Detection

AIDS: Acquired Immune Deficiency Syndrome

ARIMA: Autoregressive Integrated Moving Average

ARVI: Atmospherically resistant vegetation index

ASL: Above Sea Level

ASTER: Advanced Space-borne Thermal Emission and Reflection Radiometer

AVHRR-NOAA: Advanced Very High Resolution Radiometer National Oceanic and Atmospheric Administration

BSL: Below Sea Level

BUA: Built-Up Area

CBD: Central Business District

CGIAR: Consultative Group on International Agricultural Research

CSI: Consortium for Spatial Information

CUSUM: Cumulative sum methods

DEM: Digital Elevation Model

DHS: Demographic and Health Survey

DRC: Democratic Republic of Congo

DQ: Data Quality

DQA: Data Quality Audit

DEM: Digital Elevation Model

DVH: Distance to Vector Habitats

DW: Distance to Water

EA: Enumeration Area

FMoH: Federal Ministry of Health

GDEM: Global Digital Elevation Model

GFATM: The Global Fund to Fight AIDS, TB and Malaria

GIS: Geographical Information Systems

GPS: Global Positioning Systems

HBR: Human Biting Rate

HCF: Health Care Facility

HED: Human Ecology of Disease

HMIS: Health Management Information Systems

HRR EUMESTAT: High Resolution Radiometer European Organisation for the Exploitation of Meteorological Satellites

HSC: Health Services Commission

ICD-RHP: International Classification of Diseases and Related Health Problems

IRV: Independent Risk Variable

ISODATA: Iterative Self Organizing. Data Analysis Technique Algorithm

ITN: Insecticide-Treated Mosquito Nets

KAP: Knowledge Attitude and Practice

LG: Local Government

LGA: Local Government Area

LSMoH: Lagos State Ministry of Health

LULC: Land use Land cover

MARA: Mapping Malaria Risk in Africa

MDG: Millennium Development Goal

M&E: Monitoring and Evaluation

MODIS: Moderate Resolution Imaging Spectroradiometer

NDVI: Normalised Difference Vegetation Index

NHREC: National Health Research Ethics Committee

NMCP: Nigerian National Malaria Control Program

OR: Odds Ratio

PCA: Principal Component Analysis

RBM: Roll Back Malaria

RC: Randomised Control

RDQA: Routine Data Quality Assessment

RH: Relative humidity

SA: Supervisory Area

SAP: System Assessment Protocol

SAVI: Soil Adjusted Vegetation Index

SDS: Service Delivery Sites

SRTM: Shuttle Radar Topographic Mission

STEMIS: Spatio-Temporal Malaria Information System

SSA: Sub-Saharan Africa

SVI: Spectral Vegetation Index

TB: Tuberculosis

TSB: Treatment-Seeking Behaviour

TWI: Topographic Wetness Index

USGS: United States Geological Survey

U5: Under Five

VC: Vectorial Capacity

VCU: Vector Control Unit

WHO: World Health Organization

WMR: World Malaria Report

WRBU: Walter Reed Biosystematics Unit

Chapter One: Introduction

1.1 Introduction

Urban malaria as noted by Baudon and Spiegel (2003) is the malaria of the future Africa. While much is known about rural malaria, little is known about the ecology of urban malaria, particularly in areas that depict the African urban locations of tomorrow (Brieger *et al.*, 2001). This thesis investigates the environmental and socio-cultural risks¹ of urban malaria in households in a cross-sectional study in Lagos state, Nigeria. Nigeria is home to Lagos, Africa's largest urban agglomeration, and it is also the nation with the highest malaria burden (UNDESA, 2012; WHO, 2012a). By 2015, Lagos state is projected to be the 14th largest agglomeration in the world (UNDESA, 2012). My research will identify risk factors important for urban malaria in Lagos state from a broad range of them and through it further a deeper knowledge of its ecology in this location and that will yield specific policies for the disease reduction.

Though the World Health Organization (WHO) reports a global recession in malaria of approximately 17% and 26% in cases and deaths respectively between 2000 and 2010, and current estimates for 2010 are about 219 million cases of malaria and 660,000 deaths (WHO, 2012a); however, this is not the case in Lagos state, Nigeria, the case study site for this research. Between the years 2000 and 2011, the total number of malaria cases increased by 77.3% and cases of malaria in pregnancy rose by 124.3% over the last five years of this period (LSMoH, 2010; 2011). Despite the decreasing global figures on the burden of malaria, according to WHO (2012a), this decrease represent only 10% of the true scale. There are still local cases which are missed due to poor surveillance systems at local, national and regional levels (WHO, 2011b; 2012a; 2012b). This implies that the downturn recorded globally may be otherwise at smaller scales, which is made obvious in the figures reported in this case study site.

¹ This describes that observable part of the human culture that draws on cultural precepts, economic constraints, social norms and individual psychology. It is used interchangeably in this thesis to mean the same as behaviour.

My thesis draws on the theory of human ecology of disease to examine risks and patterns of urban malaria at fine geographic scale as depicted by this study location. While the ecology of malaria in rural areas has been much studied (Deressa *et al.*, 2007; WHO, 2012a), evidence on the urban ecology is limited. In the past, malaria was considered a predominantly rural disease (Klinkenberg *et al.*, 2005). The reason for this is that urbanisation protects from disease, owing to the greater affluence in urban populations in urban areas that affords them the use of mosquito protection; pollution from urbanisation, affecting larval habitats and life-cycle of mosquitoes; and higher human density, leading to lower biting rates (Robert *et al.*, 2003), focusing research and interventions to only rural locations. However, with urbanisation in Africa has come the opposite, what Endsjö (1973) calls “urbanisation with economic progress but no development”. There is mounting evidence of rapid population increase, urban poverty and deteriorating health and municipal infrastructure, unplanned development and increasing indulgence in rural livelihoods within urban locations (Afrane *et al.*, 2004; Klinkenberg *et al.*, 2005). This creates opportunities for vector breeding in a population with relatively low immunity (Trape and Zoulani, 1987). As such, many African cities are unable to cope with the consequences of this ecological change.

The concern for the consequences of the rapid urbanisation in Africa² has increased the involvement of scholars in urban malaria research in Sub-Saharan Africa. These include Klinkenberg *et al.* (2005) (study in Accra, Ghana); Wang *et al.* (2006a; 2006b) (study in Dar es Salaam, Tanzania and Abidjan, Cote d’Ivoire respectively); Nahum *et al.* (2010) (study in Cotonou, Benin); and Ngom and Siegmund (2010) (study in Yaoundé, Cameroon). While they have individually examined a broad range of variables, making important contributions to knowledge, the studies are still limited in their consideration of an integrated range of important factors for the future. Owing to their current situations, they are still not able to give an account of what may be expected in Africa by mid-century, should population continue to increase at the estimated rate.

In Lagos, Nigeria, which currently represents the urban Africa of tomorrow, studies have focused on socio-cultural aspects of paediatric malaria and caregivers (Brieger *et al.*, 2001); prevalence of pregnancy malaria (Agomo *et al.*, 2009); malariometric

² Currently, there are two megacities with population of about 11.2 million. By 2025, these megacities will remain; Lagos, as one of them, will increase in population to 18.9 million. The number of urban agglomerations with populations between 5 and 10 million will rise from one to seven, those with 1 to 5 million persons from 40 to 71 and those with 500,000 to 1 million persons from 44 to 71 between 2011 and 2025. Therefore, by 2035, over 50% of the Sub-Saharan African population will live in cities. Lagos’s urbanisation rate is about 3.7%; the majority of other cities have a rate of less than 1%, but by 2050, Africa’s urbanisation rate will triple (UNDESA, 2012)

surveys of peri-urban Lagos (Aina *et al.*, 2013) and vector entomology (Oyewole and Awolola, 2006; Okwa *et al.*, 2007) with little or no emphasis on an integrated range of ecological factors with potential to increase malaria in urban locations. Nigeria is still one of the highest carriers of the disease and of the death burden in Africa and globally, with Lagos being one of the highest contributors in the country (FMoH, 2005; 2006; RBM, 2008; WHO, 2012a). Nigeria's current urban rural proportion is 49%, which is about the average predicted across Africa for 2035³ (UNDESA, 2012).

1.2 Burden and Trends in Malaria Transmission

Malaria, a parasitic disease caused by the bite of an infected anopheles mosquito, continues to be a major public health problem. There are 104 malaria-endemic countries, and 79 of them are classified as being in the malaria control phase with ongoing transmission (WHO, 2012a). Amongst these endemic countries, Nigeria and the Democratic Republic of the Congo (DRC) account for over 40% of estimated deaths, and these countries together with India account for over 40% of cases globally. Approximately 174 million of these cases (81%) and 91% of deaths occur in Sub-Saharan Africa, mostly of children under five years (WHO, 2011b; 2012b). From this, Nigeria accounts for about 25% of cases and over 35% of global deaths (see Figure 1).

Hospital reports by Lagos State Ministry of Health (LSMoH, 2011) show that malaria accounts for over 60% of outpatient visits, and is responsible for the 30% and 11% mortality rates in children under five years and pregnant women respectively. The state contributes the highest figures in the south-west zone, which accounts for the majority (50%) of the Nigerian malaria burden, with the lowest contribution from the south-east zone (28%) (FMoH, 2005; Mouzin *et al.*, 2012).

After over a century's worth of investment in research and intervention efforts at eradication and control by international and national agencies, WHO has currently set a target to achieve 75% global reduction in malaria cases by 2015. Currently, 50 countries are on track to achieve this, but Nigeria and DRC are yet to record any reduction in malaria cases, unlike India which is predicted to record a decrease of about 50 to 75% in incidence between 2000 and 2015 (WHO, 2012a). According to WHO (2012a), progress in more than one-third of tropical developing countries of which Nigeria is part

³ The proportion of urban rural population in Africa is currently estimated at 40% and is expected to increase to 50% by 2035 (UNDESA, 2012)

cannot be assessed. WHO believes that the limitation in data availability inhibits evaluation.

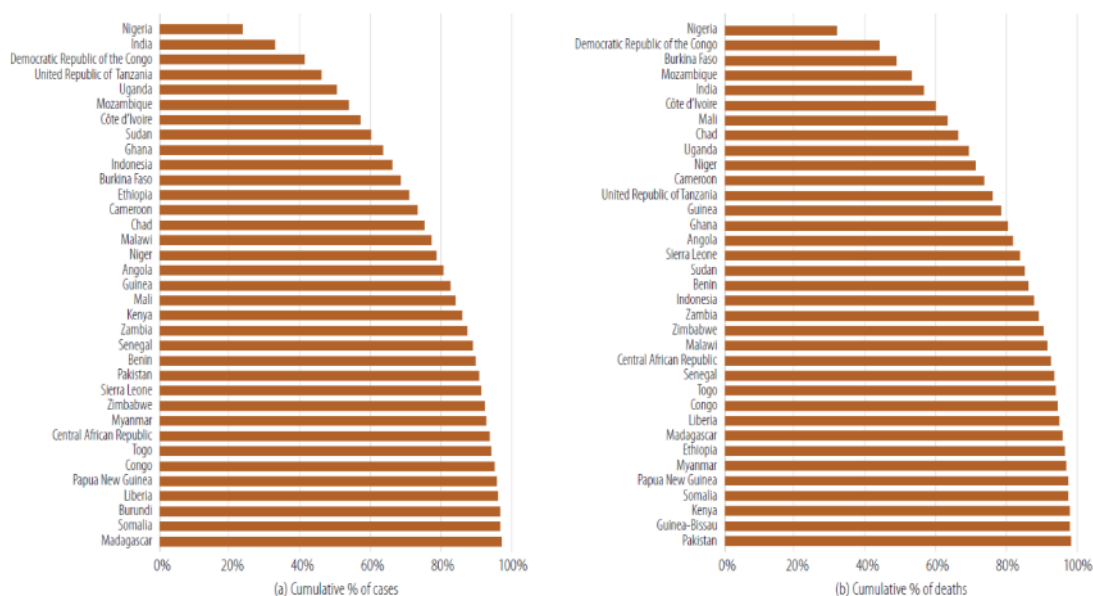


Figure 1: Cumulative proportion of the global estimated cases and deaths accounted for by countries with the highest number of (a) cases and (b) deaths

Source: World Malaria Report (WHO, 2012a)

Data available to WHO (2012a) (in Figure 2) shows that while a gradual decrease has been recorded in deaths and severe cases of malaria, the number of confirmed malaria cases continues to increase in Nigeria; this is also the case in Lagos state (LSMoH, 2010; 2011; WHO, 2012a).

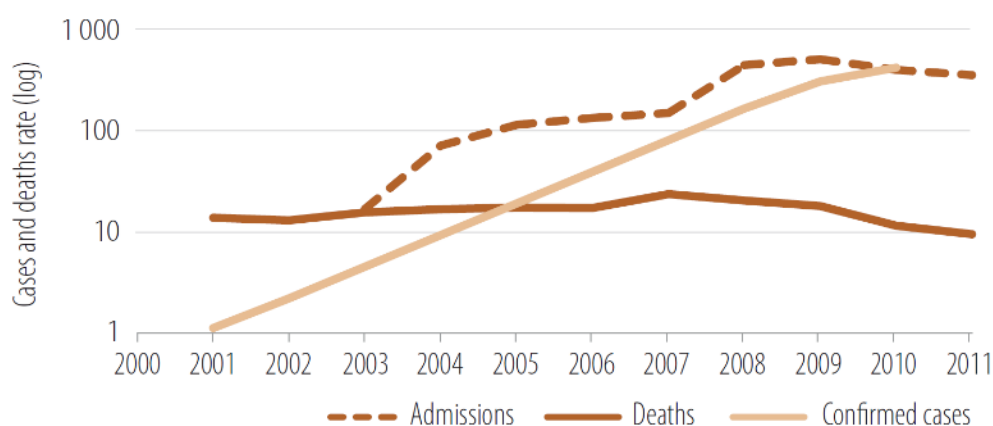


Figure 2: Microscopically confirmed cases, admissions and deaths from malaria (per 100,000) in Nigeria

Source: World Malaria Report 2012 (WHO, 2012a)

Though Nigeria reports a higher prevalence of malaria in rural (48%) than in urban areas (23%) (Mouzin *et al.*, 2012), this is not in doubt as malaria has been established as a rural disease (WHO, 2012a). What is of concern is that by mid-century, Sub-Saharan Africa will be almost as urbanised as current Lagos, Nigeria (UNDESA, 2012). As such, the urban malaria burden, globally estimated at 25% (Keiser *et al.*, 2004), may be exacerbated. To avert this, Nigeria, and in particular Lagos state, are important areas to begin to understand the urban ecology of the disease towards its future prevention in Sub-Saharan Africa. According to WHO (2012a), meeting the stated international target to reduce 75% of the malaria burden depends on achieving substantial gains in the highest-burden countries, of which Nigeria tops the list. Examining this state and country, which currently depict the future urban situation in Sub-Saharan Africa, presents an important point for study. This will increase knowledge of the ecological characteristics of the locality and urban malaria in general through the application of relevant theoretical frameworks.

1.3 Theoretical Strands

From the body of studies on the ecology of malaria, three dominant theoretical frameworks have been applied for the understanding of the disease.

Early studies adopt a landscape epidemiological approach based on Pavlosky's theory of natural focality of disease (Pavlovsky, 1966). The foci of infectious diseases are analysed by delimiting vector habitats through the examination of vegetation, climate and other elements of the physical environment and natural landscapes and linking them to vectorial risk indices and malaria transmission patterns (Mutuku *et al.*, 2009; Machault *et al.*, 2010), but they contain little that are cultural.

Another group of studies employ a socio-ecological lens to study how behavioural attributes that include culture, knowledge, education, religion and migration influence malaria risk patterns as well as health behaviour, without reference to environmental and natural factors connected to vector presence (Njama *et al.*, 2003; Oresanya *et al.*, 2008).

The third group of studies utilise a human ecology of disease framework to examine both socio-cultural and environmental factors such as proximity to anopheles habitats, topographical characteristics, housing, travel history, climate, agriculture, religion, preventative behaviour, education, knowledge, attitude and practice associated with malaria risks (Afrane *et al.*, 2004; Klinkenberg *et al.*, 2005).

Evidence from studies points consistently to certain factors that have been associated with increased incidence of malaria in urban areas such as migration and travel history, housing and preventative behaviours and proximity to vector breeding habitats, identified to include agriculture and open drains (Klinkenberg *et al.*, 2005; Ye *et al.*, 2008; Baragatti *et al.*, 2009; Yamamoto *et al.*, 2010). While the importance of these risk factors in increasing malaria have been revealed in earlier studies, local variations in risk factors and the way they influence disease patterns do occur (Hay *et al.*, 1998b), and little is known about whether these are relevant single/combined factors that could address the malaria situation in the city centre of Lagos, Nigeria, such that a significant reduction could be recorded in the location of highest burden that could trigger a significant global success. Other factors such as working at night, partaking in night-time activities without protection, and the way a broad range of variables interact in urban locations have not been particularly studied.

My research, therefore, intends to bridge this gap. I employ the dominant lens of human ecology of disease to examine the ecology of malaria in urban Lagos state through a broad range of risk factors.

1.4 Statement of Research

The overall aim of my research is to study, explain and understand the ecology of urban malaria in a case study location of Lagos state, Nigeria and through it identify important risk factors for the disease in this location. This is implemented at two levels: through the analysis of clinical malaria infection in Lagos state and the investigation of the influence of environmental and socio-cultural variables on malaria risk in Ikeja and Kosofe local government areas (LGA).

As part of the research process, I develop spatial databases at both the meso (Lagos state) and the micro levels (Ikeja and Kosofe LGAs) linking both environmental and socio-cultural variables. I achieved this by using mixed methods in a two- stage cross-sectional study protocol. The databases form the basis of my thesis upon which all analysis is conducted in order to answer my research questions.

At the meso scale (Lagos state), I examine the quality of clinical malaria infection data reported by the LS MoH over the period 2000–2009. I assess the temporal trends of these data sets during the same time period using a qualitative approach. In addition, I explore the spatio-temporal trends in clinical malaria in order to visualise, identify and select locations of elevated rate of disease, such as Ikeja and Kosofe LGAs, that later

form the in-depth focus of this research. I further this investigation at this scale to examine the relationship between meteorological variables and clinical malaria infection. This is to understand the influence of climate on biological and entomological processes taking place in the disease cycle in Ikeja and Kosofe LGAs, an urban centre in Lagos state. It is currently assessed to be an urban heat island⁴ (BNRCC, 2012) and one of the locations with an elevated malaria rate. I advance this knowledge in urban malaria at the location (Ikeja-Kosofe), and probe local processes of environmental and socio-cultural importance and their contribution to malaria occurrence in households. I identify variables of both statistical and public health significance and describe their role in influencing urban malaria infection supported by the human expressions of place.

In setting out this overall aim, my research will answer these questions through the research objective stated under each research question below.

1.4.1 Research Question 1

In what ways do socio-cultural and environmental risk factors impact on the patterns of urban malaria? How are these patterns revealed? Why are these risk factors important?

1.4.1.1 Research objectives

- To explore and visualise the spatial and temporal patterns of clinical malaria cases in Lagos state, identifying locations with elevated disease rates
- To examine the relationship between clinical malaria and meteorological variables in Ikeja and Kosofe LGAs;
- To investigate the urban malaria risks in relation to environmental and behavioural (socio-cultural) exposures in households in Ikeja and Kosofe LGAs.

1.4.2 Research Question 2

How reliable is the malaria data reported through the Lagos State Ministry of Health (LSMoH)?

⁴ Lagos is currently experiencing a temperature increase of 0.04°C per annum and an annual increase in rainfall of 15cm, a two-week increase in the length of the rainy season, and extremely hot days (with the temperature exceeding 38°C).

1.4.2.1 Research objective

- To examine the quality of clinical malaria infection data and its management and reporting system in Lagos state-owned health care facilities

1.5 Research Methods

To achieve these research objectives, my strategy as depicted in Figure 3 was to first explore the malaria infection data produced by routine data collecting health care facilities (HCFs) in Lagos state. This was to identify an appropriate location for the in-depth study. In doing so, I identified a location where the study applied a two-phase cross-sectional approach primarily focused on gathering and analysing data on households. It consisted of a pilot study and a main study that employed a mixed-methods approach made up of a semi-structured interview, GIS, remote sensing, and a questionnaire survey. I used the results of the semi-structured interview conducted during the pilot stage to improve and develop a questionnaire survey employed in the main study as well as to enhance the interpretation of the quantitative relationships (Tashakkori and Teddlie, 2003).

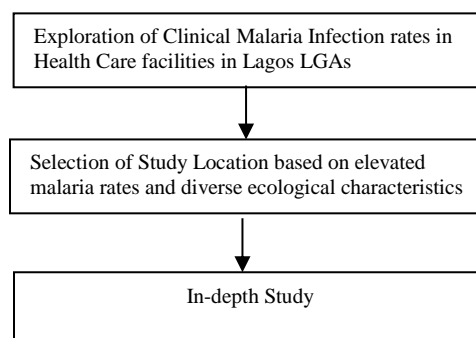


Figure 3: Research strategy

Mixed methods are advantageous because they utilise quantitative methods to quantify malaria risk relationships and qualitative methods to capture and voice human experiences of disease and place (Johnson and Onwuegbuzie, 2004; Creswell, 2009). While they enhance the development and improvement of the quality of the research instruments used for this research, they are resource demanding, and there is often loss of information during the qualitative to quantitative data conversion process (converting semi-structured interview transcripts to close-ended questions in the questionnaire). Despite this, employing a mixed-methods approach in this research allows it to engage

with the evolving sub-discipline of medical and health geography (Entikin, 1991; Kearns, 1993).

Apart from the household survey, my research also relies on purposively collected secondary sources of malaria infection data, climate data, entomological information and GIS datasets to assess malaria risk relationships (White, 2010). The malaria infection data is explored spatio-temporally using a density approach to identify areas of elevated disease rates such that they become a focus for further investigation. I explore the resulting environmental and socio-cultural datasets associated with malaria risks using familiar geographical techniques in ways to further our understanding of urban malaria and human experiences. These approaches include GIS and statistical methods, image processing techniques and content analysis. In all these, my main data analytical techniques are logistic regression (Hosmer and Lemeshow, 2000), limited to only binary outcome datasets; time-lagged correlation, to examine malaria–climate relationships (Zhang *et al.*, 2010); content analysis, a quantitative approach to analyse textual data with the weakness for information loss (Bazeley, 2003; Bryman, 2012); an adapted version of the Global Fund for Aids Tuberculosis and Malaria Data Quality Audit (GFATM DQA) tool to assess the quality of malaria infection data (GFATM, 2009); and GIS analysis to develop and examine trends in quantitative data (Jerrett *et al.*, 2010; Cromley and McLafferty, 2012).

Embarking on a pilot study prior to a larger project can provide insight to possible difficulties (Lackey *et al.*, 1998); however, not all flaws of a major project show up at that stage. According to Treece and Treece (1986) and Lackey *et al.* (1998), a pilot study does not provide all answers, because it is an artificial situation, with limited scope, a small sample size, and above all the ensuing context not anticipated in a larger study can override all earlier stated reasons.

I hope that by using a mixed-methods approach in this research, I will not only engage with the evolvments in the sub-discipline of health and medical geography but shed light on the much deeper complexity of the disease often not captured by a single method.

1.6 Significance of Study

My study provides a basis for evidence-based research into the complexity of urban malaria from multiple perspectives. It employs the human ecology of disease framework, a dominant theory of the sub-discipline of health and medical geography, to

address a disease of present and future significance in the most urbanised location of Africa. This has academic and policy-based significance.

The thesis applies mixed methods to derive two spatial database products that did not previously exist: a macro-scale spatio-temporal malaria information system for Lagos state and a micro-scale spatial database on household malaria risks and its environmental and socio-cultural variables of Ikeja and Kosofe LGAs. These databases will be examined through the development and assessment of predictive models that will reveal important pathways for disease exposures in the urban environment of Lagos state and locations with similar characteristics. With this, there will thus be new contributions to knowledge such as using the theoretical framework and narrowing down on important risk factors in Lagos state, with theoretical, methodological and empirical significances.

This study will also contribute to the evidence needed to better understand the urban ecology of malaria in Lagos state. It will therefore reveal more facts regarding the suspected malaria burden that Africa is likely to face by mid-century and beyond, thereby using such knowledge to plan and reduce the impact of this future crisis. This will support public health decision-making and future disease management through its conclusions that derive from the use of these databases. These could initiate progress into further studies.

1.7 Thesis Structure

For coherence purposes, my thesis is structured around nine chapters (including this one) as presented in Figure 4, it shows the way each chapter relates to the others. Though Chapters Two and Three are dedicated to the review of literature on malaria, other chapters continue to recount scholarly evidence that justifies the elements of the research.

Chapter One: Introduction

Chapter One introduces my research by discussing the theme of the study, the research objectives and the thesis's significance, as well as its outline.

Chapter Two: Geography of Malaria

In Chapter Two, I examine fundamental concepts in health and medical geography and the way they relate to the geography of malaria. I also discuss main theoretical strands

employed in the study of malaria and establish the existing research in Lagos. I progress to describe the biological and behavioural aspects of the vector mosquito and the way they relate and coincide with human behaviours.

Chapter Three: Human Ecology of Malaria

Here I present a literature review of urban malaria studies, employing a human ecology of disease analytical framework to discuss the determinants of the disease under two broad themes, environment and behaviour, that represent the socio-cultural aspects of humans. I identify important variables that will be further examined in my research. I review quality issues with malaria data and its reporting system. I conclude this chapter by summarising gaps in the literature, introducing the theoretical framework that will guide the data collection and analysis stages of this research and in so doing test and apply theory in this case study.

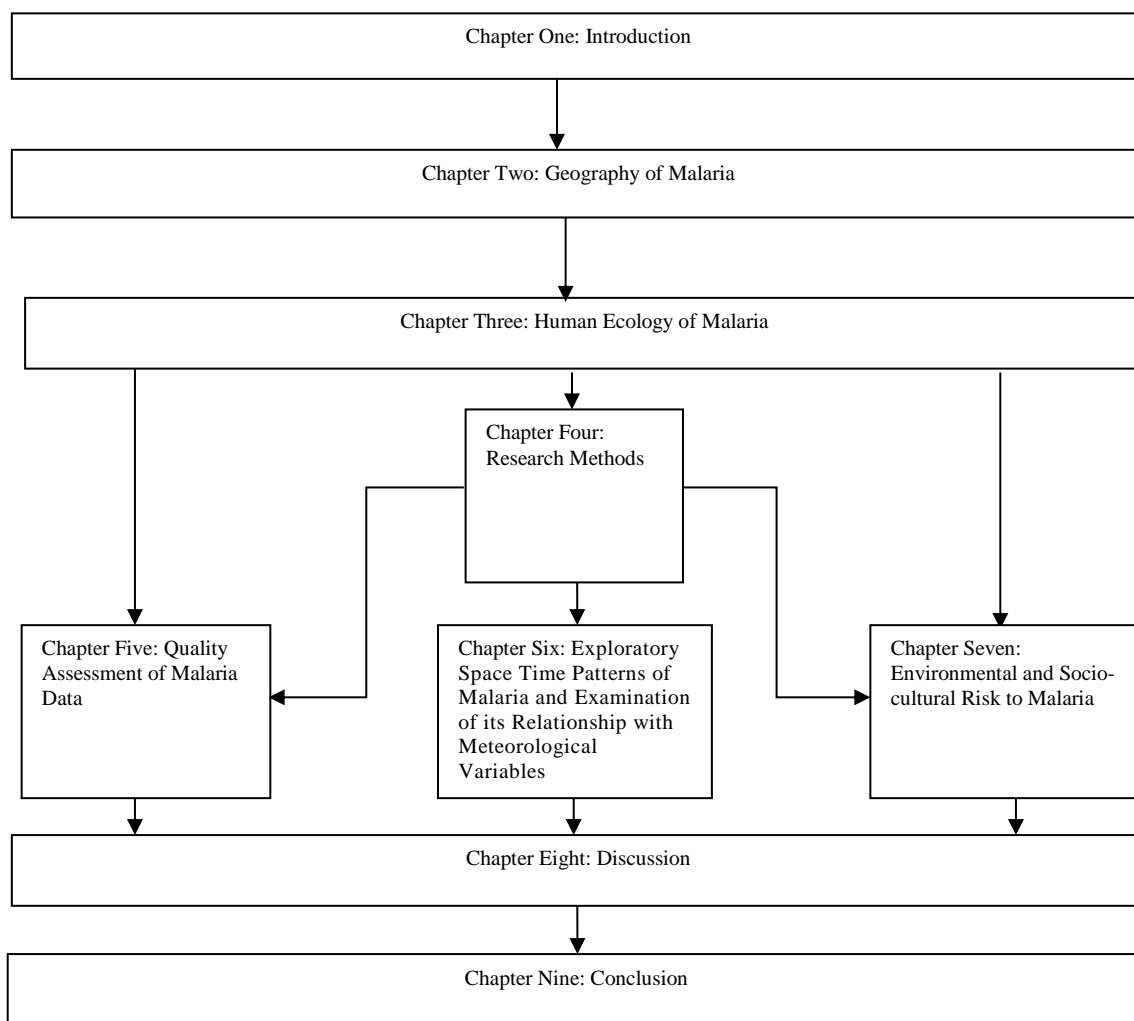


Figure 4: Structure of the thesis

Chapter Four: Research Methods

In Chapter Four I present a contextual description of the study area. I discuss and justify the research design and the study populations for the pilot and main studies. I describe the research instruments, the resulting datasets and measures, data collection and analysis methods. I consider the contribution of the feedback from the pilot study on the main study. I conclude with sections on fieldwork experiences and ethics.

Chapter Five: Quality Assessment of Malaria Data

Chapter Five responds to the first research objective by assessing the quality of routinely collected clinical malaria infection data from Lagos state health care facilities using a modified version of the Global Fund to fight against AIDS, TB and malaria data quality (GFATM DQ) assessment tool.

Chapter Six: Exploratory Space Time Patterns of Malaria and Examination of its Relationship with Meteorological Variables

In Chapter Six I explore temporal and spatio-temporal patterns in clinical malaria from 25 health care facilities using a density-based approach as employed by GeoTIME software. It details the steps used to identify LGAs with elevated malaria incidence and in so doing ascertain a location for further studies. I also present results of a time-lagged analysis of the relationship between malaria infection and meteorological variables.

Chapter Seven: Environmental and Socio-Cultural Risks to Urban Malaria

This chapter examines the ecology of urban malaria in households in Ikeja and Kosofe LGAs by developing and assessing ten predictive models containing 26 environmental and socio-cultural variables. The best quality model is selected using the Akaike Information Criteria (AIC) value.

Chapter Eight: Discussion

This is an overall discussion chapter that revisits the research objectives, summarises the thesis and draws together the main findings, strength and limitations of the research.

Chapter Nine: Conclusion

The final chapter of the thesis (chapter nine) discusses my contributions to knowledge and future research directions. It also reiterates the limitations of the research.

1.8 Conclusion

This chapter has set the scene for this research work by introducing the thesis of the research, the research objectives and the significance of the study. It summarises the main findings and contributions to knowledge and presents the thesis structure that runs through the research work. The next chapter focuses on the geography of malaria touching on fundamental concepts of health and medical geography, theories and studies in Nigeria.

Chapter Two: Geography of Malaria

2.1 Introduction

Malaria is a disease that has established itself in tropical regions of the world owing to the favourable environmental and socio-cultural characteristics peculiar to the region. This tropical concentration has brought about various meanings of place to humans that even when judged globally have different significances at multiple spatial scales.

The purpose of this chapter is not to give an exhaustive review of fundamental concepts of health and medical geography as this will be too broad a remit to achieve here. The focus rather is on concepts related to common theoretical frameworks through which the geography of urban malaria is discussed and how it contributes to variations at multiple scales. The chapter outlines the literature search strategy and consciously summarises studies of the disease in Nigeria and Lagos state without going into the clinical and medical aspects. The chapter concludes with a description of the vector biology and population dynamics. The primary concern of my research is malaria as the health outcome and its associated risk variables and this will be reflected throughout the discussions in the chapter and where otherwise, will be noted.

2.2 Fundamental Concepts of Health and Medical Geography

Often the relationship between risk variables and malaria are place and scale specific and as such, human experiences and findings differ significantly at multiple spatial scales. This section focuses on “*Place*” and “*Scale*” and their meaning for malaria.

2.2.1 *Place*

Despite the schism that characterised sub-disciplinary changes in health and medical geography (see Kearns and Moon, 2002), what has remained consistent is place, a fundamental concept of the sub-discipline. The awareness of place as a socially constructed concept has been the point of argument for a reformed medical geography

(Kearns, 1993). Its importance dates as far back as 400BC when Hippocrates wrote about “*Airs, waters, places*” (in Buck, 1988) and recently in May’s (1960) thoughts on “*disease, space, geographical and cultural location*” that remind us once again of the role of “place” in disease–human–environment interactions. Throughout their empirical work, they report how rate and distribution of disease vary with environmental characteristics of place. Today, this relationship has been exploited more than ever in diverse ways to proffer solutions for many diseases including malaria.

As Gatrell and Elliott (2009) state, “places are locations charged with meaning for which we have an attachment, i.e. points on the earth of varying spatial scales and size about which we have a collective memory and consciousness”. Place, while having a location such as home, hospital, nation and continent, contributes qualitatively to the health and wellbeing of humans. From a disease ecology perspective, Mayer and Meade, (1994) describe place as not only space but that which integrates numerous social, economic, behavioural, cultural, environmental and biological aspects of human existence to create disease patterns in specific “*places*” and specific times. This means no two places are the same, they are unique in their different characteristics as also noted by Jessop *et al.* (2008) and Jones and Woods (2013). Cummins *et al.* (2007) extend this discussion by describing place through a relational thinking process where “place” is not static or simple but rather a complex wave of interactions of human within which a human–environment disease can be investigated. Thus, places are different and can be represented quantitatively and experienced qualitatively, an “*in between*” as advocated by Entrikin (1991, p.5). Through this, we engage in qualitative and quantitative methodological debates in the sub-discipline as well as appreciating the importance of creating knowledge of places. Some studies such as Brieger *et al.* (2001) and Githinji (2009) in Nigeria and Kenya respectively employ this “in between” and relational understanding of “*Place*” in malaria–environment interaction studies.

For this research, place is thus where humans interact with the environment in measurable ways that have consequences for proliferation of malaria and overall health (Gatrell and Elliott, 2009; Meade and Emch, 2010) with the interaction and consequences being unique to places. The scale at which we represent “*Place*” brings different meanings for disease patterns and can be beyond our control, as it is often limited by spatial data availability and methodological applications.

2.2.2 *Scale*

Health data, for example on malaria, is often considered at macro level (e.g. state or national level) and with limited spatial attributes. This is largely because of the absence of routinely available small-area (locality) or individual spatially constructed data and, to a lesser degree, due to a lack of appropriate spatial analysis skills or awareness of data generators/custodians. This is evident in WHO global reports on malaria recession that often do not tidy up with figures reported at smaller spatial scales. What this means is that monitoring and targeting is being undertaken at relatively crude geographical scales which are often too coarse to reveal local patterns in malaria incidence (for example, as stated in section 1.1).

Ecological characteristics are spatially heterogeneous, and their constituent patterns at coarse scales may become irrelevant at a smaller locality, and vice versa (Gatrell and Elliott, 2009; Meade and Emch, 2010). It is thus debatable at what point a locality (study area) becomes so large that it is “global” rather than “local” such that we can interchange and relate findings at multiple scales. This is not often the case in the way certain variables assert local importance but are only significant at global scales and vice versa. However, a key advantage accrues when analysing disease patterns at a micro scale, because this facilitates focus on key problems and areas rather than relying on averages of a nation or state which have no links to appropriate corresponding data or meaning for understanding of the disease at another spatial scale.

Another problem faced in Nigeria is the availability of data on various variables at comparable spatial scales. In many instances health data is aggregated and not geocoded, thus interest in micro-scaled studies entails that the researcher generates her own data. Generating one’s data has the advantage of focusing on the problem of interest, individualising knowledge, intensifying data collection, thereby optimising and increasing knowledge on “*place*” – the locality which could otherwise have been omitted in macro-scale studies. Thus, choosing a study focus in this research work was often not predetermined by the appropriateness of scale, but interest in a key disease and key location and the way such knowledge will contribute to global discourses.

Even though scale and place can make research findings specific, such evidence still provides a basis to understand a research problem in similar locations, such that we can build on this knowledge. The next section discusses the strategy by which studies on urban malaria in similar context are identified from literature.

2.3 Literature Search Strategy

The intention of this literature search is to establish what has been done on urban malaria and identify common theoretical frameworks employed in its geographical understanding.

The thesis is concerned broadly with the ecology of malaria where a multiple interaction of factors influence the disease and it is also concerned with data quality issues. Such relevant literature has been published under a variety of subject disciplines. The broadness of geography, and in particular, health and medical geography, the sub-discipline under which this thesis falls, is such that it has no single dedicated literature database. My research objectives cover different areas and I have explored various strategies to find the relevant literatures.

As this thesis is geography-based, I have not lost sight of my intended contribution to the discipline and the sub-discipline in particular. In view of this, I have employed an “*in between*s” strategy of narrative and systematic review (Collins and Fauser, 2005; Petticrew and Roberts, 2006). The literature search strategy employs relevant variables associated with the overarching framework of disease ecology and intended research objectives as key words in the search. The disease ecology is a dominant framework used in understanding human–environment–disease interactions.

As stated earlier, my literature search has not been a linear process, neither has it always included search terms. Owing to the fact that I had to review literature on Lagos and Nigeria separately, as well as discuss quality issues with malaria infection data, each search strategy was different. While I have used subject-specific online databases, I have worked with supervisor suggestions, sourced articles through sources such as local libraries, publications and conferences in Nigeria which do not have the luxury of an electronic database, followed lists of references from journal articles, books and advice from Nigerian and international conferences I have attended. All sources are combined and efforts are presented as a flow chart in Figure 5.

In more detail, I have searched using Google Scholar, sciences, social sciences, health and life sciences subject databases. The databases are the Social Sciences Citation Index (SSCI), Sciences Citation Index (SCI), Applied Social Sciences Index and Abstract (ASSIA), Social Sciences and Humanities (SSH), Health Sciences (HSC), Life Sciences on the Proquest, Scopus and Web of Knowledge gateways, the WHO library catalogue and local publications in Nigeria. I identified keywords from the human ecology of

disease theoretical framework (see figure 6) (Meade and Emch, 2010); those that have been translated for urban malaria by Robert *et al.* (2003) (see figure 7) and from reviews on urban malaria (Warren *et al.*, 1999; Wang *et al.*, 2006b; De Silva and Marshall, 2012). I applied the key words (*urban malaria or malaria*) AND any of the following specific key terms at a time or similar terms in multiples (*disease ecology, ecology, knowledge attitude and practice (KAP), knowledge, culture, belief, occupation, education, wealth, income, expenditure, behaviour, age, ethnicity, religion, migration, travel history, vegetation, habitat, topography, elevation, slope, aspect, curvature, climate, meteorology, temperature, rainfall, relative humidity, Normalised Difference Vegetation Index (NDVI), housing, agriculture, animals*). This was an iterative process as new key words derived from the search are re-applied. I searched these variables with an additional term (*Nigeria and Lagos*) to establish Lagos, Nigeria studies. I also searched for (*data quality, data assessment, accuracy, GFATM⁵*). A final total of 3,246 articles were obtained and the subsequent process of excluding irrelevant articles to review only 82 articles on malaria incidence, 35 supporting articles and 47 on malaria data quality is presented as Figure 5.

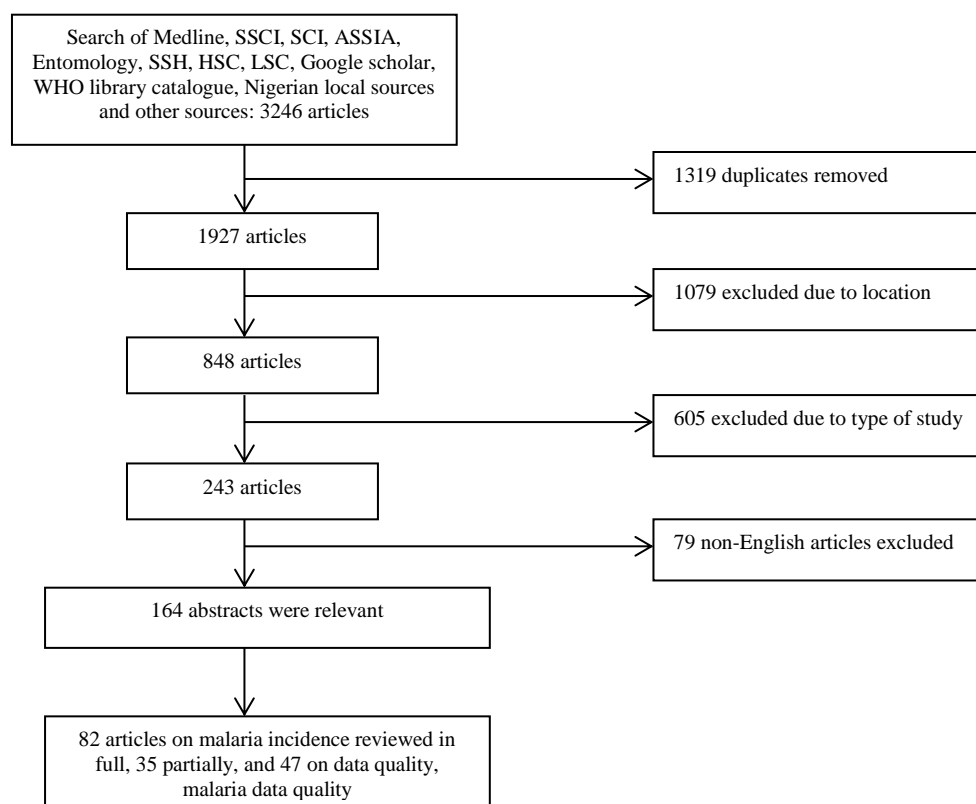


Figure 5: Literature search strategy

⁵ Global Fund to Fight AIDS, Tuberculosis and Malaria

After the download of all references, I first eliminated 1319 duplicate studies from 3246 articles which arose from the way the search was applied to individual subject databases that held similar articles, leaving 1927 articles; In the next stage, I excluded 1079 studies from the 1927 articles where the focus was on rural areas, non-tropical, westernised countries or generalist articles that did not have a study focus or that concentrate on animals leaving 848 articles. From the 848 articles, I then removed 605 studies that centred on the anopheles vector which were beyond the study scope. As experimental study designs are not that common, I do not differentiate them in this research but rather focus on the perspectives being brought in by the different designs. I identified Nigerian and Lagos studies to clarify what has and has not been done. This left 243 articles. As there are many studies in English which would give a good summary of urban malaria, I excluded 79 non-English studies from 243 articles to arrive at 164 relevant abstracts.

This was an iterative process, and I often went back to the initial search results to hand-pick relevant articles which I had come across in the list of references, or which pertained to the anopheles or a rural study location, or clarified some perspectives in the review process. I integrated this with recommendations from other sources mentioned earlier, either as part of the final studies reviewed or as supporting articles. The 164 articles include was 82 fully reviewed studies, 35 partially reviewed on malaria infection and another 47 on data quality (partially and fully reviewed).

Even though the literature search was not a linear process, it covered the length and breadth of all relevant databases, articles and fundamental textbooks that will form the basis of the studies and text discussed in the remaining of this chapter and the subsequent chapter on the ecology of urban malaria.

The next section discusses the geography of urban malaria and commonly employed discourses in explaining its interaction with the human environment and how they integrate the fundamental concepts of place and scale discussed earlier.

2.4 The Geography of Malaria and Commonly Used Conceptual Frameworks

With about 25% of the global burden of malaria occurring in urban dwellers in Africa (Keiser *et al.*, 2004), much still needs to be understood, as past studies focused on the medical and clinical aspects and less on its geography. However, growing patterns in studies align with the trend in the sub-disciplinary changes of health and medical geography. WHO, for example, are more socially and culturally place-aware in their

research and intervention efforts than before (Heggenhougen *et al.*, 2003). They currently recommend an integrated vector, behavioural and clinical case management approach to reduce the burden and meet its millennium target.

Evidence from the literature reveals many discourses that have offered explanations on urban malaria human–environment disease interactions. This section discusses the geography of urban malaria clustered around three frequently occurring paradigms: the landscape epidemiology, socio-ecology and human ecology of disease.

2.4.1 Landscape Epidemiology Approach

In the explanation of the spatial delineations of vector-borne diseases, the landscape epidemiology approach often arises. This is based on Pavlovsky's (1966) concept of natural nidality, which states that the evolution of vector-borne diseases in humans is triggered by their penetration into a disease system contained naturally amongst wild animals. According to Pavlovsky (1966) vector species and their accompanying disease have their natural habitats known as “nidus”, and also referred to as “focus” or “region”, constrained by a naturally peculiar climate, vegetation, topography and soil and water composition characteristics that favour the development of vector and associated parasites. However, when humans intrude into this region, this destabilises the equilibrium and vectors that ordinarily feed on animals change their feeding patterns to humans and in the process infect humans (Pavlovsky, 1966). This implies that for humans to acquire a physical environment-associated disease such that they become host to parasites, they must have occupied or penetrated the “foci” or “habitat” of that disease for its benefit at an infectious time of the year. Brown *et al.* (1996) describe this as an exploitative and non-beneficial but yet mutual relationship between human and environmental microorganisms.

As regions favourable for anopheles breeding are characterised by the attributes mentioned earlier, a number of studies draw largely on the Pavlovsky (1966) theory, and while they increase knowledge about the vector biology, behaviour and attributes that encourage this density reveal little or nothing about the incidence of the disease (Trape *et al.*, 1992; Machault *et al.*, 2012). Since these physical environmental attributes are mappable, these studies utilise GIS and remote sensing techniques to regionalise and develop geographic profiles of vector and malaria transmission risk. Mauchault *et al.*'s (2010) study in Dakar, Senegal examine factors which delimit the foci of infectious,

animal–human disease, by analysing the associations of vegetation, humans, animal and insect life, soil types, climate, topography and other elements of the natural landscape.

Despite its strength, Meade (1977) accuses it of lacking socio-culturalism in consideration of individual and society, perceived exposure and cultural aspects. It is also limited in the sense that health decision-making requires the consideration of complex factors beyond just the geographical distribution and determinants of disease risk. In addition, its definition of vector habitats and supposed human intrusion stands the risk of being criticised for environmental determinism. However, many of its concepts, such as disease regions and pathogen distribution, have been integrated into the human ecology of disease framework to regionalise vector habitats as well as human interactions into these environments.

2.4.2 Socio-ecological Model

According to Stokol (1996) and Butterfield and Lewis (2002), the socio-ecological model describes the interplay and transaction between people, their behaviour, and their socio-physical environment (physical, cultural and social dimensions) over multiple spatial and temporal scales and multi levels. The theory's core principle is that the human interrelations and behaviours in social spheres and the various ways they influence health outcomes is based on personality, perceptions and economic resources. Thus, the level of congruence between people and their multi-level socio-cultural environment is an important predictor of wellbeing.

There have been an increasing number of studies adopting socio-ecological models in the examination of malaria, malaria treatment-seeking behaviours (TSB) and malaria knowledge, attitude and practice (KAP) which are primarily concerned with evaluating how aspects of education, wealth, and culture influence the uptake and utilisation of malaria intervention (Panter-Brick *et al.*, 2006; Esse *et al.*, 2008; Oresanya *et al.*, 2008). These studies have used both quantitative and qualitative methods (focus group discussions and interviews) in different locations, thus being place-sensitive. Oresanya *et al.* (2008), for example, examined the role of multiple factors in influencing the uptake of insecticide-treated bednets (ITN) with the aim of assessing progress towards the malaria Millennium Development Goal (MDG), and they found that religion, income, education and ethnicity were important community aspects that influence the level of ITN use. There are also researches applying spatial analysis to assess access, treatment-seeking behaviour and the usage of health care facilities for malaria control

(Noor *et al.*, 2003)⁶. Although these studies are important, they have not focused on the disease itself but rather on health behaviours such as the uptake of interventions to prevent the disease.

In contrast, another group of studies have assessed the influence of these behavioural aspects to the disease (Njama *et al.*, 2003; Saeed and Ahmed, 2003a). Findings reveal the differing roles of wealth, education, religion, culture and ethnicity on the incidence of the disease through the way they influence behaviour, housing types, social and recreation activities. While the role the behavioural aspects play in the uptake of interventions and the transmission of malaria disease are recognised and the role of the biological and behavioural aspects of anopheles vector downplayed, it is such that the story is “incomplete”. As Meade (1977, p. 382) puts it, the appropriateness of examining both (vector and behaviour) in this model “*is dynamically controversial*”. A more applicable method would be one that integrates the concepts from landscape epidemiology and socio-ecological models as offered by the human ecology of disease and thereby telling us a complete story.

2.4.3 The Human Ecology of Disease

The human ecology of disease is concerned with the way in which human behaviour, in its cultural and socio-economic contexts, interacts with environment to produce and prevent disease amongst susceptible people. These interactions are driven by a number of variables drawn from frameworks described earlier, which Meade and Emch (2010, p. 30) sum up under the three vertices with many overlaps, as shown in Figure 6, enclosing human health: “*habitat, population and behaviour*”. These variables are housing and settlement patterns, workplaces, health care services, transportation systems, schools and governments, individual psychology, agricultural lands, socio-economic constraints, mobility, roles, beliefs, social norms and cultural practices and technological interventions arising from education, migration, application of new knowledge and inventions, population genetic make-up, age, gender, nutritional and immunity status, and physical environment variables such as climate, water and soil composition, topography, and vegetation cover (Meade and Emch, 2010).

The framework is based on all the elements at the three vertices of human ecology of disease interacting in space and time to produce a level of health in a population.

⁶ Findings not discussed as beyond study scope

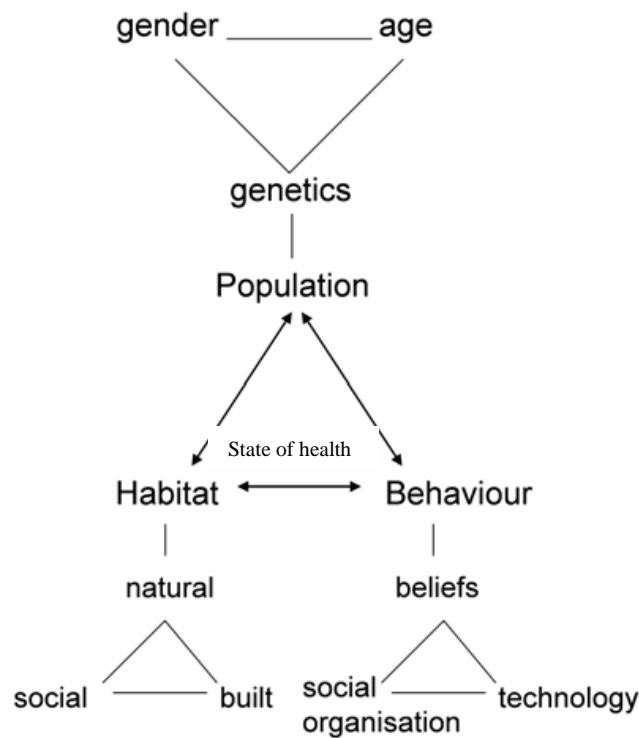


Figure 6: Triangle of human ecology of disease

Source: Meade and Emch (2010)

2.4.3.1 Health

Meade and Emch (2010) present health as not an absent or present characteristic but according to Audy's (1971) measurement of continuing property of health where everyone is at a different level. When applied to malaria, it means people may carry the parasite without falling ill whereas others with a high parasite density may eventually succumb. Across the urban malaria literature, health has been represented as health behaviour, mild or severe forms of malaria or its consequences (Koram *et al.*, 1995; Saeed and Ahmed, 2003b; Klinkenberg *et al.*, 2005; Oresanya *et al.*, 2008).

2.4.3.2 Habitat

The habitat, from Gatrell and Elliot's (2009) conceptualisation, is "place", with meaning for both the anopheles vector and humans. According to this framework, this consists of the physical, built and social environments. The physical environment is associated with variables that naturally encourage the presence of anopheles such as climate, water and soil composition, topography, vegetation cover while the social environment variables consist of social and political manifestations like health care, transportation systems, schools and governments and man-made environment variables are housing and settlement patterns, agricultural lands and workplaces.

2.4.3.3 Population

Population is concerned with the characteristics of humans as biological organisms – potential hosts of disease. According to Meade and Emch (2010) these characteristics include genetic make-up, age, gender, nutritional and immunity status, which define human ability to cope with changing environment and disease status, e.g malaria.

Children under five years, pregnant women living in malaria-prone areas and non-immune visitors to such areas have been classified as the most vulnerable populations (Agomo *et al.*, 2009; Phillips *et al.*, 2009; WHO, 2012a). Genetically, non-sickle cell carriers are more likely to develop and experience devastating consequences from malaria compared to sickle cell carriers (Nahum *et al.*, 2010).

2.4.3.4 Behaviour

Humans, as cultural beings, partake in daily behaviours that alter their habitats. They construct homes, cultivate land, gain education, earn a living, take up a role, develop and employ new technologies, migrate, participate in religious and cultural activities, and through this create a belief system characterised by values and perceptions (MacCormack, 1984; Brown *et al.*, 1996). These are what Meade and Emch (2010) define as behavioural variables, which describe the observable part of human culture. Meade and Emch (2010) identifies four pathways through which there is interplay between humans, vectors, parasites and environment that have a health outcome. First, through human re-creation of the environment, thereby altering anopheles habitat conditions; second, participating in risky behaviours; third, the moving around of elements of the disease environment system (vectors and parasites) through the transportation system, during migration; fourth, the practice of cultural norms, for example, selection of one's marriage partner, with consequences for the genetic make-up of the populations.

The human ecology of disease looks at both the habitat or environmental and the social, cultural or behavioural aspects of the framework. In so doing, it sums up what the landscape epidemiology and socio-ecological models individually explore. Though Kearns (1993) initially criticised this approach as being too quantitative, in recent times, Kearns and Moon (2002) acknowledged its theoretical and methodological consistency in its representation and creation of knowledge on place over even the qualitative approaches. To understand these broad human–disease–environment interactions means to identify and measure the associated variables and evaluate their relationships.

However, they are often daunting and difficult to measure, as Meade (1977) indicates the task can oversimplify a complex disease system.

Robert *et al.* (2003) utilises the human-disease-environment approach to develop a conceptual framework for urban malaria (Figure 7). It features a range of climatic and topographic factors, entomological, land-use and demographic characteristics, individual and household factors and municipal (government) initiatives. Robert *et al.* (2003) clearly separate those variables associated with the vector from those within the power of humans to modify. The importance of these thematic range of variables that this thesis can draw on are revealed through the studies of Baragatti *et al.* (2009); Peterson *et al.* (2009) and Ngom and Siegmund (2010) discussed in the next chapter. Thus, it presents itself as a relevant framework to assess urban malaria differentiations, but across the literature many of its associated variables are still left unexamined, leaving the story on the human ecology of urban malaria incomplete. Perhaps, it is the daunting task of measuring the complex variables that has limited research.

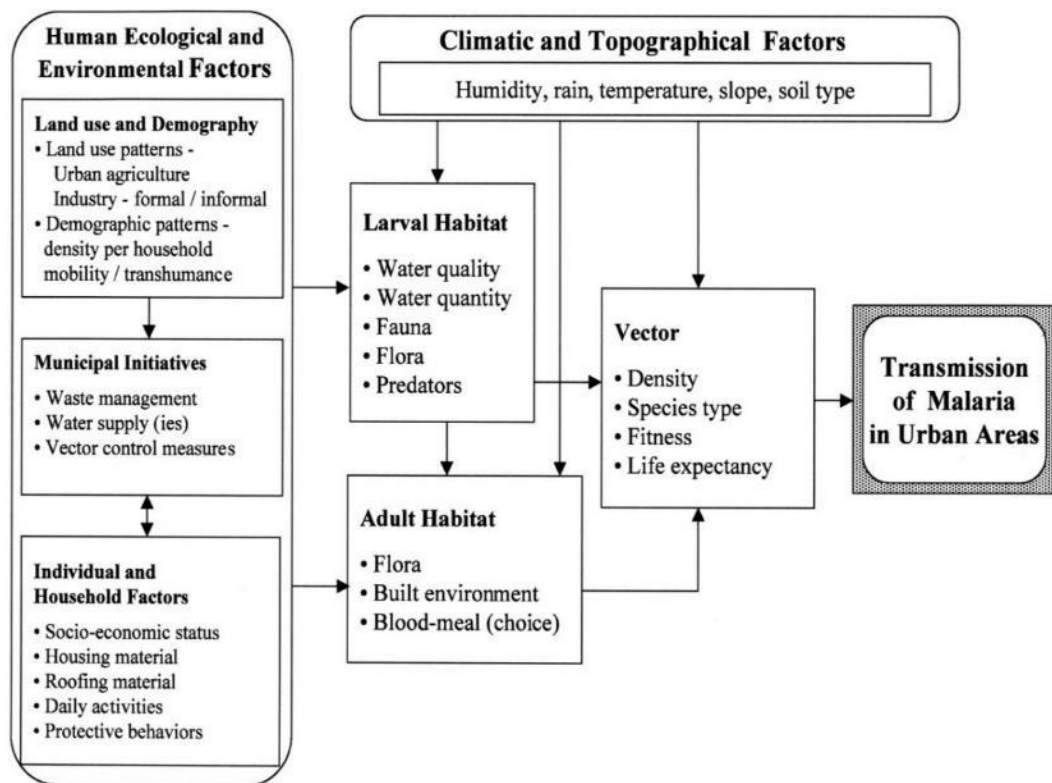


Figure 7: Conceptual framework for urban malaria transmission in Africa

Source: Robert *et al.* (2003, p.173)

The next section focuses on reviewing existing studies on Lagos, Nigeria to establish what has been done and what this research will build on to contribute to better understanding of urban malaria in the study location.

2.5 Nigerian Studies

As noted earlier and further expanded in the next chapter, this research is limited to reviewing studies where malaria is the health outcome and environmental or/and socio-cultural risks are contributory factors to the disease. While this scope is also applicable to Nigerian studies reviewed, there are very few studies that have addressed this, thereby limiting what can be synthesised in this sub review of literature. I begin by summarising studies that have gone beyond the scope of my research without going into the details of their findings while noting the trends related malaria studies have taken.

Entomological studies, studies examining factors influencing malaria TSB, KAP and studies on malaria prevalence, acquired immunities and case management conducted under clinical settings and communities are the broad group of studies that have dominated the literature on Lagos, Nigeria. As they are beyond the scope of this research, their findings are not discussed. What I note through the studies though, is the increasing awareness of the role of socio-cultural factors in TSB and KAP pre-21st century (Ogunmekan, 1983; Ekeh and Adeniyi, 1986; Brieger *et al.*, 1996) after the era of early 1930's centring on the eradication of malaria and single focus on vector control in Davey and Gordon's (1933) and Garrett-Jones and Shidrawi's (1969) studies.

Most recently in the 21st century, in the era of integrated management of disease there was more diversification of studies even though they were clinically situated, focusing on TSB or entomological studies (Okwa, 2003; Senbanjo and Opreh, 2008) and very few on malaria as the outcome. These studies were less concerned about environmental risk factors and engaged more with socio-cultural factors. In Lagos state specifically, Okwa's (2003) investigated the prevalence of malaria in pregnant women in relation to a range of socio-cultural factors including place of residence. Out of six local government areas (LGAs) examined, the findings showed that pregnant women living in most urbanised part of Lagos state which is Ikeja had the highest incidence of malaria while Lagos Island which is the commercial nerve centre of the state reported the lowest. Also Christians have the highest infection rate over Muslims and other religions. However when we think about the high rate of uptake of bednets by Christians in Nigeria as reported by Oresanya *et al.* (2008) little wonder if uptake is equivalent to usage because Okwa's (2003) recorded the highest infection rate in pregnant women using bednets as a preventative option over use of others like screen doors/windows, mosquito repellents and elimination of breeding sites. Women in genetic blood groups

A and O appear to be very susceptible to malaria with the genotype A having the highest rate of malaria. None of the studies examined the prevalence rates of malaria in Nigerian ethnic tribes and my research intends to explore it.

More recent studies have examined the relationship between malaria and environmental factors. These studies are outside of Lagos state and I highlight some of their concerns. The studies of Ediang *et al.*, (2005), Ayeni (2011) and Omonijo *et al.*, (2011) report the influence of climate change on clinical malaria patterns in parts of Nigeria but with little or no explanation for the observed trends. Those by Ifatimehin *et al.*, (2009) and Njar *et al.*, (2013), in Kogi and Cross Rivers states respectively, applied quantitative analysis to assess and map malaria disease transmission in relation to environmental risk. While the studies attempted to examine housing characteristics, proximity to various anopheles breeding habitats and malaria, they are methodologically flawed, with no real attempt to appropriately measure population health, physical and social environmental risk factors. One such study is that by Oluleye and Akinbobola (2010) in Lagos state. This study assessed only the temporal patterns of malaria disease in relation with physical environmental aspects of temperature and rainfall, without assessing the rainfall's or the time-lags' effect on the biology of the vector and, in turn, malaria, or the socio-cultural risk variables. The findings from Oluleye and Akinbobola (2010) study are discussed in the next chapter under climate.

Entomological studies by Awolola *et al.*, (2002a), Afolabi *et al.*, (2006) and Oyewole and Awolola (2006) in Lagos state reports a number of prominent anopheles mosquito behaviours, species and preferred habitats. This forms the focus of the next section.

2.6 The Anopheles Vector Mosquito and the Plasmodium Parasite

The *anopheles gambiae*, *anopheles arabiensis* and *anopheles funetus* are the major malaria vectors in Lagos, Nigeria and Sub-Saharan Africa in general, but the most efficient belongs to the *anopheles gambiae* complex (Thomson, 1948; Service, 1970; Okwa *et al.*, 2007). These vectors harbour the most fatal and commonly occurring disease parasite: *Plasmodium falciparum*, whose survival depends on the survival of the mosquito itself, which then are a function of its behaviour and the availability of appropriate habitats (Anderson *et al.*, 1996; Sinden and Gilles, 2002).

2.6.1 Habitats

Anopheles mosquitoes have a preference for natural habitats such as marshes, swamps and bodies of water. However, the difficulty of sustaining natural habitats in urban areas

has forced the adult and larval mosquitoes to adapt, breed and develop in human-induced habitats like agricultural lands and forests (Matthys *et al.*, 2006a; Olayemi *et al.*, 2011). There are temporal habitats in urban areas that are rain-and human-fed: wells, pools, puddles, hoof prints, burrow pits, ditches, tyres, tyre tracks, drains/gutters, domestic water containers and refuse dumps (Service, 2002; Okogun *et al.*, 2005; Adeleke *et al.*, 2008). Their choice by larvae and adult mosquitoes depends on the specie. For example the *anopheles melas* species has maintained its preference for salt breeding and vegetated habitats such as lagoons; orchards; crab holes; edges of mangrove swamps; rivers and streams at the Lagos coastlines (Service, 1970; Awolola *et al.*, 2002b).

2.6.2 Behaviour

The anopheles mosquitoes have a predominant behavioural pattern but under certain circumstances can also exhibit other behaviours. For example, after a human biting session, the adult anopheles mosquito settles outdoors or indoors in dark corners, under the bed, in walls, roofs, plants and vegetated surfaces. Where cattle and domestic animals are present in greater numbers than humans, they primarily feed on animals (Service and Townson, 2002) and have been found to exhibit such behaviours in Lagos state (Awolola *et al.*, 2002b; Oyewole and Awolola, 2006). The *anopheles gambiae* peak biting times are at 10pm outdoors and 3am indoors, while the *a. arabiensis* peak biting time is at 1am outdoors, but bite throughout the night indoors. The *anopheles funestus*, on the other hand, has a peak biting time of 2am outdoors and 10pm indoors (Oyewole and Awolola, 2006). In all, both indoors and outdoors, the anopheles mosquitoes persistently bite through the night.

The average life-span of the anopheles mosquito is about 10 to 14 days, but can be longer or shorter depending on climate, predation and absence of disease (Teklehaimanot *et al.*, 2004). In the temperature range between 16 and 28°C and relative humidity of 60%, they are known to effectively encourage their development to last between 9 and 10 days, but at temperatures below 16°C or above 35°C and a relative humidity less than 50%, mortality is high (Macdonald, 1957; Craig *et al.*, 1999; Service and Townson, 2002). Unlike the *anopheles gambiae*, the *a. funestus* and *a. arabiensis* have a preference for the dry season and because of their presences across seasons, both are responsible for all-year-round malaria transmission.

The behavioural and habitat characteristics of the vector and that of humans can be linked to the behavioural and habitat vertices of the human ecology of disease framework such that their coincidences become a risk for human malaria. These, when understood, can help to identify risks to humans and apply appropriate frameworks for their measurements.

2.7 Conclusion

This chapter summarises how sub-debates have shaped knowledge on urban malaria in Africa, and particularly Nigeria, and through it connect geographies of developed and developing countries to locality studies through knowledge of place (Phillips and Rosenberg, 2000; Jessop *et al.*, 2008; Jones and Woods 2013). From the studies, we noted that the spatial and temporal patterns shown by malaria are a consequence of global and local environmental and behavioural variables; we then identified the human ecology of disease framework as an encompassing theory to promote its full understanding. Despite its strength in this respect, studies that attempt to apply the framework fully for malaria in Nigeria and the wider Sub-Saharan Africa are still limited.

We observed that except for the studies by Brieger *et al.* (1996), Brieger *et al.* (2001), Oluleye and Akinbobola (2010) and Aina *et al.* (2013) on aspects of the ecology of malaria, no study, to the best of my knowledge, has been undertaken to explicitly examine the ecology of urban malaria at such a spatial scale and breadth in Lagos state that this study sets out to undertake. Progress in this area has been limited by past legislative and political freedom to freely access, collect and use relevant Nigerian datasets, but an amendment to the Nigerian Freedom of Information Act on 6th June 2011 will possibly trigger improvement in this area.

In other parts of Sub-Saharan Africa, particularly East Africa, the local ecology is different and risk factors for malaria are often not applicable to West Africa where this research is situated. The differences in localities and the fact that a one fix solution cannot address problems across “localities”, is an issue Jessop *et al.*, (2008) and Jones and Woods (2013) have recognised.

East Africa is different. It is topographically diverse with accompanying climate resulting in what is called highland malaria, i.e. epidemic, unstable seasonal malaria, limited by diverse temperature conditions in these topographically diverse regions. This is not so in West Africa where malaria is endemic, stable and occurs all year round,

though peaks may arise seasonally in specific locations. Therefore, evidence found in these other areas have not always been transferable and this lack of transferability may have contributed to the inability to record decline in many of the West African countries like Nigeria, Ghana and Cote d'Ivoire (WHO, 2012a). As the largest and emerging urban locations, e.g. Lagos, Ouagadougou, Abidjan and Freetown, are situated in West Africa and this makes it an important region to create knowledge. Thus, it is important to understand this ecology and tailor more appropriate response to this local situation.

It is obvious that there is a paucity of studies on the geography of malaria in Lagos and Nigeria, and there is a need to increase knowledge about the locality through the application of appropriate frameworks. Consequently, in the next chapter, I will employ the theory of human ecology of disease, identified earlier, as an analytical framework to identify and assess variables important for urban malaria.

Chapter Three: Human Ecology of Malaria

3.1 Introduction

A number of environmental variables have been proposed from the previous chapter to explain the regionalisation of malaria, a vector-borne disease. Although the literature covers a wide variety, this review will focus on two major themes in relation to an outcome which emerge repeatedly across the literature. These are associated with the habitat and behaviour elements and health outcome as depicted in the triangle of human ecology of disease, the most encompassing of the theoretical discourses identified in the earlier chapter to be most relevant for explaining the ecology of urban malaria.

They are: the influence of the *environment* (physical and built) in the regionalisation of anopheles habitats; human presence as translated from the *habitat* element; and the role of the *socio-cultural environment* in defining human vector contact as interpreted from the *behavioural* element of the human ecology of disease framework. These themes are related to the *population's* characteristics and *health* outcome. The study population characteristics describe the vulnerability of the population in terms of non-immune travellers, pregnant women and children under the age of five and sickle cell carriers. These all represent risk factors often appearing under the population, habitat and behavioural elements of the vertices of the human ecology of disease (HED) framework that are all translated and adopted for this study.

In the context of malaria, the health outcome frequently occurring in literature can be expressed in terms of differentials in malaria incidence; differentials in vulnerability to the consequences of infection, for example, the risks of mortality or severe malaria; or in terms of access to or use of effective means of preventing or treating malaria (Koram *et al.*, 1995; Klinkenberg *et al.*, 2005; Oresanya *et al.*, 2008). In this review, I primarily focus on the differentials in malaria incidence which has been represented in studies by a range of malariometric indices. Malariometric indices represent measures used in the

literature to represent the incidence, occurrence or probability of malaria. They include self-reported malaria and hospital based measures derived from clinical symptoms or confirmed through laboratory tests all sometimes translated to malaria burden.

The studies reviewed have applied a number of methodological approaches to identify risk variables, examine disease patterns and their contributory effects. Quantitative methods have commonly prevailed. For example, for the dichotomous outcome variable, logistic regression is applied (Alemu *et al.*, 2011); when independent variables are non-categorical, discriminant analysis is used (Omumbo *et al.*, 2005), for continuous variables, linear regression (Ra *et al.*, 2012).

In analysing temporal relationships between the disease and meteorological variables, correlation and regression have been useful as demonstrated by Ye *et al.* (2008) and Zhang *et al.* (2010). Often ARIMA (autoregressive integrated moving average) is used to remove correlation, consider time-lagged and seasonality effects and predict future occurrences of malaria (Zhang *et al.*, 2010). Zhang *et al.* (2010) study has also used qualitative graphical representations to describe temporal patterns in malaria infection.

In particular, for spatial pattern detection, global and local spatial autocorrelation methods have also featured. With reference to space-time clustering, the challenge of representing clusters as snapshots of time have persisted, and often a spatial-only approach such as Moran's I, Geary's Index and Kulldorf SaTScan is applied (Ernst *et al.*, 2006; Hui *et al.*, 2009; Bejon *et al.*, 2010; Wen *et al.*, 2011; Cromley and McLafferty, 2012), leaving the spatio-temporal story to be told through multiple timestamps of disease patterns. New methods similar to the CUSUM and employing a density approach through GeoTIME software is slow to gain grounds despite offering a single timestamp and interface for all analysis. Perhaps, its non-probabilistic exploratory space time cluster detection approach deters its common use.

For derivation of habitat measures, spatial analysis, GIS and modelling, and remote sensing functions such as measurement, surface analysis, overlay analysis and statistical analysis, band ratios, classifications have been applied on sources that include remote sensing imageries, GPS mapping (Jerrett *et al.*, 2010; Machault *et al.*, 2010). In terms of behavioural elements, while quantitative methods such as surveys are frequently applied to capture them, qualitative methods like interviews and focus groups have also been used (Tang *et al.*, 1995; Brieger *et al.*, 2001).

Studies at household and population scales are less common than at individual levels because most research tend to focus on children (less than five years) and pregnant women identified to be most vulnerable to the disease. Nevertheless, a number of important risk factors have emerged as common across these study scales and as such have not been differentiated by scale in this review unless where the findings differ. The review will follow the structure of the HED framework beginning with a summary of health outcomes; risks associated with the physical environment followed by the built environment, socio-cultural factors and some population characteristics. It will also touch on data quality issues.

3.2 Health

There are many ways to construct “*health*”. The World Health Organization (WHO) defines “*health*” as a state of complete physical, mental and social wellbeing, and not merely the absence of disease and infirmity (WHO, 1946). Meade and Emch (2010) as part of the HED framework suggest the use of Audy’s (1971) definition of “*health*” as a continuing property, i.e. a state of health measured by the ability to cope with environmental stimuli. According to Kearns (1993) and Kearns and Collins (2009) Audy’s approach centres on the biomedical disease-oriented model while WHO definition is encompassing and appears to capture a broad positive orientation that shifts away from this biomedical approach to representation centred around human potentials.

As stated in the introductory section, health in this review will focus on a range of malariometric indices which represent differentials in malaria occurrence. Thus, in the context of malaria, it has been represented both biomedically and humanistically. Current malaria indicators used by WHO to monitor and evaluate intervention impacts are broadly categorised under reported malaria, health service delivery and intervention coverage (WHO, 2012a) which Kearns and Collins (2009) classify as humanistic and representing a positive outcome. Common measures which emerge consistently across malaria literature are: differentials in malaria occurrence (Ye *et al.*, 2008); differentials in vulnerability to the consequences of infection – for example, risk of mortality, complications of severe malaria (Greenwood *et al.*, 1987); or in terms of access to or use of an effective means of preventing or treating malaria (Rashed *et al.*, 2000).

3.3 Physical Environment

The physical environment consists of characteristics such as climate, topography, land use and land cover (LULC) and vegetation conditions (Meade and Emch, 2010). Climate seems to be particularly influential amongst these characteristics. For example, climate is a function of topography and as well it can influence vegetation, LULC types. Vegetation types and LULC also influence evapo-transpiration within a climatic cycle creating a micro climate condition. These ensuing interrelated and complex relationships make it difficult to tease out the individual roles of these physical environmental variables on malaria risks.

3.3.1 Climate

A number of studies exploit the direct link between these commonly applied meteorological variables (temperature, rainfall, relative humidity, sunshine) and anopheles mosquitoes (Ye *et al.*, 2008); while others examine the anopheles density and the number of malaria cases it translates to (Ye *et al.*, 2008); and others investigate the indirect relationship with malaria cases (Zhang *et al.*, 2010). Secondary sources provide easy access to long-term climate and malaria infection data to exploit this relationship over experimental designs where the abundance and infectivity of the anopheles mosquito can be monitored, but this has the disadvantage of data with poor temporal resolution (monthly instead of daily datasets), and as such, the effect experienced in days is often not captured or modelled. On the other hand, embarking on experimental designs is expensive and not often feasible for monitoring long-term impacts. It also assumes that the abundance of vectors that emerge from enabling climate conditions and their infectivity are translated into higher cases of malaria without taking into account that human behaviours can interrupt this relationship. Findings from these associations as discussed subsequently have been a point of debate in the last century.

3.3.1.1 Climate-Malaria Debate

Climate has been established by many authors such as Craig *et al.* (2004b) and Zhang *et al.* (2010) to have a relationship with malaria. This is through the way rainfall influences ecological and habitat changes and how temperature determines the longevity of vector and parasite with possible consequences for the disease spread. This relationship has been taken beyond just the association of similar trends in these variables to be identified as a main determinant of increased malaria and its resurgence in highlands Africa. This territorial expansion of malaria is the reason behind the climate-malaria debate.

The climate malaria debate is concerned with the resurgence of malaria in previously free malaria zones of highland Africa. According to Lindsay and Martens (1998); Martens (1999) and Tanser *et al.* (2003) transmission were rare, sporadic and unstable but in recent times increased frequencies of disease and changes in patterns have occurred. Patz *et al.* (1996); Epstein *et al.* (1998); Lindsay and Martens (1998); Martens (1999); Kovats *et al.* (2001) and Tanser *et al.* (2003) argue that the increases are a consequence of 0.6°C increment in global temperature that has occurred in the last century (Houghton *et al.*, 2001). On the other hand, Craig *et al.* (2004b); Chaves and Koenraadt (2010) and Stern *et al.* (2011) assert that though a relationship exists between climate and malaria, it is more complex than imagined by the earlier authors due to multivariate factors that are demographic and social working hand in hand with climate. This is supported by Mouchet *et al.* (1998) and Hay *et al.* (2002a) who contend that malaria increment also occurred in areas of stable malaria and lowland areas like West Africa where climate is less at variance and even resurged due to drug resistance at the Thai-Myanmar-Cambodia borders (Na-Bangchang and Congpuong, 2007). It is argued that factors other than climate play a role in the disease spread and more importantly at small geographic locations. They include drug resistance of the plasmodium, population and urbanisation, cross border migration, poor health provision, vector control, land use changes and culture (Hay *et al.*, 2002b; Craig *et al.*, 2004a; Craig *et al.*, 2004b; Ye *et al.*, 2008; Chaves and Koenraadt, 2010).

Recent global malaria maps developed by Gething *et al.* (2010) show that areas reported to experience rises in temperatures coincide with areas where intervention strategies have successfully reduced the malaria burden. These debates thus re-assert the need to examine other aspects of the environment and human influence at smaller spatial scales and localities. This study intends to examine these while acknowledging the role of the anopheles described in the previous chapter in the malaria climate relationship.

3.3.1.2 Climatic Conditions necessary for the Anopheles Mosquitoes Development

According to Service and Townson (2002), appropriate climatic conditions are necessary for the survival and abundance of the anopheles mosquitoes. Rainfall, relative humidity and temperature are noted to be relevant for their survival, but the overarching importance of temperature persists. Paaijmans *et al.* (2010) say that the availability of moisture through rainfall influences transmission while temperature acts as a regulatory force that determines to a large extent the mosquito's survival and abundance. Further, Macdonald (1957); Craig *et al.* (1999); Service and Townson (2002) clearly establishes

that mosquitoes will survive between 16 and 35°C where relative humidity is as low as 50%. This translates to their survival lasting between 9 to 10 days within that temperature range. However at an optimum temperature range of between 20 to 25°C and an accompanying relative humidity of 60% survival can extend to 10 to 14 days meaning higher abundance of mosquitoes and a possible increase in number of malaria cases (Paaijmans *et al.*, 2010). At temperatures below 16°C or above 35°C and relative humidity less than 50%, mortality is high and survival time is less than 9 days (Craig *et al.*, 1999) and above 40°C the survival rate is zero (Craig *et al.*, 1999; Okogun *et al.*, 2005; Fournet *et al.*, 2010). These decrease the density and abundance of mosquitoes with possible implications for decreased malaria incidence. Similar climatic conditions have occurred in Lagos, Nigeria.

A number of studies have examined the relationship between anopheles mosquito characteristics and climatic conditions and possible associations have ensued for increased abundance, densities with possible consequences for higher human biting rates with more humans being infected leading to increased malaria incidence. I acknowledge that a direct relationship exists between these but indirectly with malaria. The scope of this research and review of literature focuses on studies examining the indirect relationship between malariometric indices and climatic variables.

3.3.1.3 Temperature

When we examine the relation between malaria and temperature and even other meteorological variables, it is the non-linear and indirect relationship that we exploit.

This temperature relation has been the study focus in a number of peri-urban and urban areas (Ye *et al.*, 2008; Zhang *et al.*, 2010; Tay *et al.*, 2012) but more focus at broad spatial scales (Craig *et al.*, 1999; Teklehaimanot *et al.*, 2004; Omumbo *et al.*, 2005). They use data on mean, maximum, minimum or weighted mean, derived daily, monthly, bi-weekly or seasonally from meteorological stations and/or meteorological satellite remote sensing imageries of differing spatial resolutions such as Meteosat 4–6, AVHRR-NOAA⁷ or the HRR-EUMETSAT⁸ (Hay *et al.*, 1998b; Rogers *et al.*, 2002). The studies have related the variables to malaria incidence with datasets at daily, weekly, bi-monthly, monthly, seasonally or annual temporal nature from the vulnerable population (children, pregnant women, non-immune travellers) or the general

⁷ AVHRR-NOAA: Advanced Very High Resolution Radiometer – National Oceanic and Atmospheric Administration.

⁸ HRR-EUMETSAT: High Resolution Radiometer-European Organisation for the Exploitation of Meteorological Satellites.

population from clinical settings, and analysed them by applying different time-lags specific to data. Temperatures at which the relationship is significant have ranged from 22°C to 27°C across studies (Craig *et al.*, 1999; Ye *et al.*, 2008).

What the key findings establish can be summarised in one statement: a form of relationship exists between temperature and malaria, but in urban areas this has been inconsistent. Also, a consensus on the single most valuable temperature predictor has not been reached across the studies, as the locations have varied ecologically and used different temperature and malariometric measures. These findings presented in the next paragraphs.

For example, in Teklehaimanot *et al.*'s (2004) ten-year study in the highlands of Ethiopia using the time-lagged regression method in urban areas differentiated by altitudes above and below 1700m: in areas located above 1700m, the minimum weekly temperature is positively associated with the number of malaria cases, with a significant increase extending from seven to ten weeks prior to cases and the size of the effect growing in magnitude over that range. In contrast, in areas below 1700m, the minimum temperature has an immediate small non-significant positive effect on the number of malaria cases, which stabilises over a longer time-lag to become statistically significant. The maximum temperature is not significant at any altitude. As areas on topographic altitudes above 1700m depict temperate-like colder climates, similarly, in the temperate city of Jinan, China, Zhang *et al.*'s (2010) study reports a significant positive relationship between the minimum monthly temperature and malaria cases per month at four weeks' time-lag, and also records an immediate impact and similar patterns even with the maximum temperature, in contrast with Teklehaimanot *et al.*'s (2004) earlier stated findings. On the other hand, Tay *et al.*'s (2012) findings in a population-based study in the urban centre of Kumasi, Ghana are similar to those of Teklehaimanot *et al.* (2004) on the non-immediate impact of the maximum temperature on malaria cases with up to 12 weeks' time-lag in the general population. However these studies differ in their findings on the impact of minimum temperature on malaria. While Teklehaimanot *et al.* (2004) report an immediate significant positive increase in malaria cases following an increase in minimum temperature, Tay *et al.* (2012) record an immediate inverse relationship, non-significant impact until after eight weeks, when a small positive impact is reported.

In peri-urban areas, the influence of minimum temperature on clinical malaria cases is also inconsistent. In Tay *et al.* (2012) study, the minimum temperature has a negative relationship with clinical malaria at 0, 1 and 3 months' time-lags, but not at 2 months' time-lag, where there was no impact. Maximum temperature did not have any statistically influential relationship with malaria for any time-lag except at one month, where there was a non-significant decrease in malaria cases. In Ye *et al.*'s (2008) study in the peri-urban town of Nouna, Burkina Faso, the risk of *plasmodium falciparum* infection increased in a paediatric population, as did anopheles densities, with an increase in the mean monthly temperature to between 23°C and 27°C, after which a negative relationship occurs. Using 27°C as a reference point, Ye *et al.* (2008) demonstrated that temperature above 27°C led to a significant increase in the mortality of anopheles mosquitoes and a decrease in *P. falciparum* infection, and at temperatures below 23°C, there was a risk reduction of about 53%.

On a broader spatial scale, Craig *et al.*'s (2004b) 30-year population based study in South Africa, found only the mean maximum daily temperatures from January to October of the preceding season to be significant with daily malaria cases; they were not significant with the total cases per month. Rakotomanana *et al.*'s (2010) one-year study in Madagascar did not find any relationship between the mean monthly temperature and clinical malaria incident rates even at maximum temperature levels of 26°C.

These findings confirm my earlier statement that some form of relationship exists. In summary, they demonstrate that while the effect of temperature is experienced at multiple spatial scales, the urban based studies such as those by Zhang *et al.* (2010); Teklehaimanot *et al.* (2004); Tay *et al.* (2012) are inconclusive because the local ecologies have differed in terms of temperate locations and topographic influences as well as malariometric measures applied. The paucity of studies and understanding of urban locations in Africa in particular, show that more needs to be known on the influence of climate in such ecologies, particularly using long-term data.

3.3.1.4 Rainfall

According to Hoshen and Morse (2004) and Cator *et al.* (2013), the relation between malaria transmission and rainfall is best studied when temperature is not limiting, or when urban wastewater create alternate habitat sources that may trigger mosquito numbers, or under intense rainfall that may wash away habitats causing temporary

disruptions in their survivals and development and thus obscure the already indirect relationship between malaria and rainfall.

The onset or occurrence of the smallest amount of rain has been associated with increased vector densities and malaria cases in urban and peri-urban areas, even under dry-season conditions (Adeleke *et al.*, 2008; Ye *et al.*, 2008) and the abundance of anopheles mosquitoes from these, vary by species. Mbogo *et al.*'s (2003) and Fillinger *et al.*'s (2004) studies demonstrate these anopheles-rainfall relationship⁹. Current studies on the malaria–rainfall relation do not discount these factual relationships, but simply builds on them to understand how it translates to increase malaria incidence. In urban areas, though, such research is limited.

Just like temperature, rainfall has been studied using different measures: total rainfall amount, weighted total, average by month or season, rainfall intensity, and rainfall duration, derived from meteorological stations and/or meteorological satellite imageries, as a direct predictor of malaria incidence in a number of urban and peri-urban areas (Hay *et al.*, 1998b; Rogers *et al.*, 2002). Key findings show that in many instances the relationship between rainfall and malaria incidence is not always present (Shanks *et al.*, 2002; Teklehaimanot *et al.*, 2004) and where significant relationships occur, the measures, temporal characteristics, minimum amount of rainfall required and duration has varied (Craig *et al.*, 2004b; Ye *et al.*, 2008; Oluleye and Akinbobola, 2010). More discussion follows.

Most associations between rainfall and malaria occur at a certain baseline rainfall value and are often accompanied with an underlying accompanying temperature of above 23°C (Ye *et al.*, 2008). Craig *et al.* (1999) argue that for stable malaria transmission to occur, rainfall of at least 80mm is required for at least five months with accompanying temperatures of about 22°C. Craig *et al.* (1999) goes further, proving that one month's rainfall above 80mm is not sufficient for any significant malaria transmission to occur, irrespective of temperature level. On the contrary, Ye *et al.*'s (2008) study shows that one month's rainfall of 100mm triggered a significant transmission relationship up to 160mm at temperature ranges between 23°C and 27°C. Similarly, Fournet *et al.* (2010) report that rainfall as low as 2.3mm and as high as 200mm maintained at temperatures above 25°C triggered malaria transmission at all times of the year in Ouagadougou. The findings differ but yet indicate that the reference point for rainfall amount beyond which

⁹ The anopheles climate relationship studies go beyond the scope of this review and findings are not discussed

to assess its impact is localised. Ye *et al.* (2008) peri-urban area study suggests the highest amount of observed rainfall in any location as a reference point to assess its impact on malaria infection. In Ye *et al.* (2008) study the findings showed that under a four-week lag time, every 10mm of rain above 160mm as the reference point triggered about a 4% increase in malaria infection under a temperature of 23°C.

Findings from Teklehaimanot *et al.* (2004) and Tay *et al.* (2012) studies similarly report an immediate non-progressive increase in malaria cases with increasing rainfall amount/duration. As the rainy season progresses, Oluleye and Akinbobola (2010) and Tay *et al.* (2012) record an increasingly negative relationship between malaria and rainfall in urban areas, with rainfall developing an abrupt positive relationship with malaria with the approach of the dry season in Oluleye and Akinbobola (2010) study. In Tay *et al.*'s (2012) study in a peri-urban location, rainfall is immediately negatively associated with monthly counts of clinical malaria infection, after which an increasing positive relationship is recorded and becomes statistically significant after two months.

These findings are inconsistent with each other and it can be argued that they result from the dissimilar ecological characteristics and study focuses. However, they provide some evidence on the often erratic relationship between malaria and rainfall and the overarching influence of temperature, although more evidence is needed to prove or disprove these findings in urban areas.

3.3.1.5 Relative Humidity

According to Okogun *et al.* (2005), under high temperature conditions, relative humidity helps reduce desiccation of anopheles breeding habitats, thereby prolonging their lifespans and survival rates. This relationship with malaria incidence and anopheles density as stated earlier has not always been a linear one.

Background studies by Okogun *et al.* (2005), Himeidan and El Rayah (2008), Ye *et al.* (2008) and Imbahale *et al.* (2012) show a positive relationship exists between larval densities and relative humidity and this varies with the season, with the wet season having higher larval densities. In a similar study by Rishikesh *et al.* (1985), indoor resting densities of adult anopheles mosquitoes have a positive relationship with relative humidity, but this can differ across species types, as noted by Minakawa *et al.* (2002), and this indirect relation can determine level of disease transmission.

As a direct predictor of malaria incidence in urban areas, the findings on relative humidity have been similarly inconsistent like rainfall. While Ye *et al.* (2008) and Zhang *et al.* (2010) found relative humidity to have a significantly positive impact on incidence of malaria at one and two months' time-lags, Himeidan *et al.* (2007) and Tay *et al.* (2012) did not find any immediate or progressive significant impact. Tay *et al.* (2012), however, report a positive significant impact on malaria in a rural location at the one-month time-lag, but none at two or three months. Ye *et al.*'s (2008) and Tay *et al.*'s (2012) studies in peri-urban locations established 60% as the optimum relative humidity value, above which its impact on malaria increased exponentially when there is an accompanying optimum temperature range between 27.9°C and 30°C.

Though this research focuses on reviewing studies on malaria, it notes the climate–malaria relationship studies attempts to reveal the indirect and complex association that occur between the anopheles vector, malaria incidence and meteorological variables and the role that temperature plays in the overall relationship. A summary of the findings from studies discussed earlier show that though temperature is represented by different indices, it has been more consistent in its association with malaria incidence when compared to other primary meteorological variables such as rainfall and relative humidity. Evidence from studies reviewed earlier shows that in regions where rainfall and relative humidity are as low as 0mm and 21% respectively and occur in as short a time as one month, anopheles will breed and increase rapidly in short developmental cycles, provided the appropriate temperatures prevail (Craig *et al.*, 1999; Okogun *et al.*, 2005; Fournet *et al.*, 2010). Such circumstances could either lead to epidemic, seasonal or perennial malaria situations. However, when temperatures are above 22°C with rainfall as low as 80mm and relative humidity at about 60% occurring over a period of five months, this will promote stable malaria conditions common in non-topographically diverse locations.

Based on the above, what we take away from the review is that while other climatic variables are equally significant under different circumstances, temperature has been more consistent, significant and possibly the best predictor of the relationship between malaria and climate in urban areas; however, what remains to be clarified is the most appropriate measure as determined by the ecological situation of the case study location.

This thesis will contribute to knowledge in this respect by replicating these studies to examine malaria and multiple meteorological variables in an urban centre characterised

by high temperatures known to be detrimental to the survival of anopheles, yet record high malaria infection rates (Oluleye and Akinbobola, 2010; Tay *et al.*, 2012). The thesis will build on Oluleye and Akinbobola's (2010) (see rainfall section 3.2.1.3) limited study in Lagos state; this study investigates only 60 years' average rainfall and temperature in relation to 14 years' average malaria over 12 calendar months. My thesis will examine multiple climatic variables at different time-lags in a specific microclimate urban centre location in Lagos state, using longer-term monthly climatic and disease data, not long term averages such as in Oluleye and Akinbobola's (2010) study.

3.3.2 Land Use and Land Cover (LULC) and Vegetation

Land use and land cover (LULC) measure different aspects of the earth's surface. While land use is related to the human use of land and manifests socio-economic and cultural functions such as agriculture, housing, industry and man-made vegetation, land cover describes naturally occurring aspects of the earth's surface including natural vegetation and water bodies (Stefani *et al.*, 2013). Vegetation, on the other hand, includes both man-made and natural vegetation – in fact, anywhere covered with green vegetation, in essence making it a LULC type. In urban centres, man-made, natural vegetation and other land-use types have been found to exist (Robert *et al.*, 2003).

LULC and vegetation cover, broadly categorised, represent either natural or artificial habitats of the anopheles mosquito. They depict microclimate conditions characterised with favourable temperature and humidity. These conditions make them preferred sites for anopheles mosquito resting, breeding and shelter, which has the potential to harbour and influence the behaviour of the mosquitoes (Pavlovsky, 1966; Clements, 1999; Matthys *et al.*, 2006a). The occurrence and distribution of these habitats are measured by field sampling and/or remote sensing methods (Kitron, 1998; Jacob *et al.*, 2005; Okogun *et al.*, 2005; Rongneparut *et al.*, 2005; Manh *et al.*, 2011). While field sampling methods are considered the first option in defining the presence of habitats, they can be resource consuming (Stefani *et al.*, 2013). Recent developments in landscape approach use remote sensing and Geographical Information Systems (GIS) as a less resource-intensive method to capture these habitats.

The presence of LULC as applied in malaria risk studies has been mapped from a number of remote sensing imageries. The most common are: aerial photographs (Mushinzimana *et al.*, 2006), Landsat (Masuoka *et al.*, 2003; Mushinzimana *et al.*, 2006), Ikonos (Masuoka *et al.*, 2003; Mutuku *et al.*, 2009; Krefis *et al.*, 2011),

QuickBird (Jacob *et al.*, 2007; Machault *et al.*, 2010), NOAA-AVHRR¹⁰ (Hay *et al.*, 1998b), MODIS¹¹ (Texier *et al.*, 2013) and Spot imageries (Machault *et al.*, 2010). The imageries listed all have their strengths and weaknesses. Ikonos, Spot and QuickBird are commercial imageries and have a spatial resolution of 1m to 4m, 2.5m to 10m, and 0.61m respectively. These fine resolutions mean that surface features as small as 0.61m can be captured with precision but with the Spot imagery, LULC features the size of 0.61m x 0.61m or less will be missed. Landsat, NOAA-AVHRR and MODIS are free but have coarser spatial resolutions of 30m, 8km and 250m respectively.

The remote sensing imageries mentioned earlier have the advantage of a high spatial resolution and can capture fine LULC and vegetation details in comparison to the others but come at a high cost such that the free imageries are more frequently employed in many malaria studies using LULC and vegetation as proxies for vector presence.

3.3.2.1 Land Use and Land Cover (LULC)

Land use and land cover (LULC) types are commonly derived from remote sensing imageries using supervised classification methods such as maximum likelihood (Masuoka *et al.*, 2003; Brooker *et al.*, 2004; Krefis *et al.*, 2011) or unsupervised classification, like the Iterative Self Organizing Data Analysis Technique (ISODATA) (Thomson *et al.*, 1999; Jacob *et al.*, 2007). In supervised classification methods, each image pixel is allocated to pre-defined class categories by means of training datasets (Hay *et al.*, 1998a). The method requires pre-knowledge of the study terrain and pre-specified class categories. Unsupervised classification assumes no prior knowledge of the study terrain and classification categories. It examines a large number of unknown pixels and divides them into classes based on the natural grouping present in the image values without using specified training data (Lillesand *et al.*, 2004).

By their very nature, certain LULC types exhibit features favourable for anopheles breeding; for example, five LULC types have been identified to be related to larval breeding. In order of decreasing strength of association they are: agricultural lands, swamps, water bodies, grasslands and shrubs (Masuoka *et al.*, 2003; Sithiprasasna *et al.*, 2005; Mutuku *et al.*, 2009). A number of studies have examined the relationship between malaria incidence and proximity to these defined LULC classes in both urban and rural locations. These relationships have been consistently significant. Githinji *et*

¹⁰ AVHRR-NOAA: Advanced Very High Resolution Radiometer – National Oceanic and Atmospheric Administration.

¹¹ MODIS: Moderate Resolution Imaging Spectro radiometer.

al. 's (2009) study in a rural area, and Peterson *et al.* 's (2009) study in an urban location, reveal the importance of these vector-based habitat variables in predicting the occurrence of disease. As put forward by Krefis *et al.* (2011), what this means is that households in close proximity to these LULC types are at higher risk of malaria through higher probability of human contact with anopheles mosquitoes.

Agricultural lands have featured prominently as an important factor in the proliferation of the disease in urban areas, owing to rural–urban migration and the need to maintain a source of livelihood within this region. According to Baumgartner and Belevi (2001) and Yadouléton *et al.* (2010), this causes an abundance of vectors and focal malaria transmission in places in close proximity to agricultural sites. Mushinzimana *et al.*'s (2006) study disproves part of the relationship between the LULC as vector habitats identified earlier and malaria. In the study, a negative relationship exists between rivers/streams and forest land cover, and anopheles breeding habitats with possible implications for level of malaria incidence. The explanation for this is likely that the anopheles species prevalent in this study location do not favour such habitat types. Another reason may be the suitability of the LULC classification method adopted such that it misclassifies LULC classes. Another approach is the application of vegetation indices, which is reported by Jacob *et al.* (2007) and Machault *et al.* (2010) to be more effective in discriminating agricultural fields, irrigated lands and vegetation surfaces as well as capturing climatic influences. Agricultural land, as an important LULC type in urban locations, will be discussed in a separate section.

3.3.2.2 Vegetation

Several studies have shown that vegetation cover can be used to estimate anopheles densities, distribution and transmission risk (Gaudart *et al.*, 2009; Machault *et al.*, 2010). Indices such as Soil Adjusted Vegetation Index (SAVI), Atmospheric Resistance Vegetation Index (ARVI) and Normalised Difference Vegetation Index (NDVI) have been used. NDVI, as the most frequently used, will be the focus of this review.

NDVI is a spectral vegetation index (SVI) used for mapping. This is through its quantification of green leaf vegetation coverage that is centred on the absorption and reflection of light from a vegetated surface in the red and infrared bands, respectively, of a remote sensing imagery (Campbell, 2006). NDVI is based on the premise that healthy and active vegetation will reflect more light in the infrared band than it will

absorb in the red band. It is derived by applying this formula in Equation 1 below to the red and near infrared bands of a remote sensing imagery.

$$NDVI = \frac{NIR - Red}{NIR + Red} \text{ Campbell (2006)}$$

NIR: Near Infrared

Equation 1: Formula for NDVI derivation

Healthy vegetation is not only a sign of disease absence, but also of favourable climatic conditions that promote healthy growth and photosynthesis. NDVI values indicate these characteristics and translate them from vegetation characterised by temperature and humidity conditions favourable for anopheles growth and longevity. What this also means is that while NDVI measures vegetation and other surface cover, it also acts as a surrogate measure of climate and represents the ecological characteristics of vector habitats. As Machault *et al.* (2010) state, NDVI is an index that captures the combined effects of temperature, humidity, rainfall, sunlight, altitude, land use and land cover in one value. In Hay *et al.*'s (1998b) study, NDVI has a positive relationship with the season, and further to this, it has been applied successfully by Eisele *et al.* (2003) and Gemperli *et al.* (2006) as a surrogate measure of moisture level and climatic indices. Thus, it is a useful measure to represent vegetation and land-cover types as well as climate in locations with limited meteorological stations.

NDVI has been used as a direct predictor of anopheles characteristics and malaria risks across broad spatial scales, but less often in urban locations, owing to the limited availability of high-resolution remote sensing images to capture the heterogeneous urban features at such spatial scales (Machault *et al.*, 2010). Its impact on malaria risks is also an area of limited study.

According to Patz (1998), the relationship between NDVI derived from NOAA-AVHRR imagery and the anopheles vector human biting rate is a positive one, and even when related to malaria risks and its seasons in a paediatric population in Hay *et al.*'s (1998b) study, the results remain consistent. However, this is not so in Shililu *et al.*'s (2003) and Dambach *et al.*'s (2012) recent studies attempting to predict *anopheles arabiensis* density with NDVI which report no significant impact. These inconsistencies arise for a number of reasons. As discussed earlier, NDVI is a surrogate measure of climate and also used to identify and map types of vector habitats. Hay *et al.*'s (1998b)

study applied NDVI as a measure of climate, which has an established significant relationship with malaria incidence. On the other hand, Patz (1998) relates NDVI to an evidence of human–vector contact which can be translated to the transmission of disease. However, Shililu *et al.*'s (2003) and Dambach *et al.*'s (2012) studies firstly translated NDVI into only broad habitat classes of vegetated and non-vegetated surfaces, omitting water bodies, which are a preferred habitat for *anopheles arabiensis*, which is the focus of their studies. In so doing they left out the *anopheles arabiensis* preferred habitats. Thus, the inconsistency reported when we compare Hay *et al.* (1998b), Shililu *et al.* (2003) and Dambach *et al.* (2012) studies.

NDVI applications in urban areas have many advantages. At such a fine scale, having an adequate distribution of meteorological stations to characterise microclimate condition is rare. NDVI can thus capture spatio-temporal climatic conditions at this scale that can be used to characterise the environmental features of people's activity spaces. It is also useful as a vegetation mapping device to decipher land-use classes and urban household densities (Eisele *et al.*, 2003). As a mapping tool, the NDVI values between -1 and +1 can be reclassified into land-use and land-cover types using the classification guide developed by the United States Geological Survey (USGS). According to USGS (2011), NDVI values of 0.1 and less represent water, bare surfaces, snow, ice; 0.2 to 0.5: sparse vegetation and 0.6 to 1: dense vegetation. Thus, when applied in urban areas, it serves a dual purpose: to map land use and land cover (LULC) and vegetation classes, as well as being a surrogate measure to capture finer-scale climatic conditions.

Most studies have examined this surrogate of climate, vegetation and earth cover characteristics more in relation to the vector density and abundance than to the disease. Eisele *et al.*'s (2003) and Machault *et al.*'s (2010) studies in urban areas revealed a positive significant relationship with *anopheles* density and aggressiveness and NDVI. In addition, lower NDVI values were significantly related with increased household densities (Eisele *et al.*, 2003) and thus a lower risk of malaria infection and vice versa. Across the literature we note that an NDVI baseline value of 0.35 has been established above which an increase in malaria infection is recorded (Hay *et al.*, 1998b; Texier *et al.*, 2013). In fact Hay *et al.*'s (1998b) recorded a 5% increase in total annual paediatric cases with higher NDVI values associated with the rainy season. This is because of NDVI's association with higher moisture content that produce more habitats, thus

greater abundance of vectors and with higher probability of higher biting rates and thus malaria cases.

Despite its advantages, the NDVI measure is hardly exploited for malaria studies in urban areas, despite its confirmed significance and advantage in capturing climatic conditions, vegetation and land use at such fine scale (Machault *et al.*, 2010). Most studies as discussed earlier have applied it to anopheles presence without extending it to the disease.

This research will employ NDVI as a measure for multiple variables such as vegetation and land-cover types, and a proxy measure for climate to characterise vector presence and how it relates to the occurrence of malaria.

3.3.3 Topography

Topography is characterised commonly by elevation, aspect, slope and curvature characteristics of the earth's surface. It is one of the environmental elements that determine distribution of anopheles habitats, its population dynamics, and often malaria risk patterns. According to Nmor *et al.* (2013) it has the fundamental importance of controlling surface water flow and pooling. Just like climate, it is consistently reported to have a relationship with the disease risk and transmission patterns in areas with predominantly diverse topographic features such as East Africa (Balls *et al.*, 2004; Zhou *et al.*, 2005; Cohen *et al.*, 2008). This is because of the way climatic factors vary with elevation, and of course with a previously established relationship between climate and malaria, topographic factors such as elevation will portray an indirect yet significant relationship with the disease. Higher elevations are associated with lower temperatures, lower rainfall and in turn lower relative humidity, and thus poor environmental conditions that cannot sustain anopheles longevity and parasite development. Elevation and slope have direct effects on surface water flow, since water flows from high to low elevations. Flat slopes and valley like land shapes, on the other hand, accumulate water, encourage vegetation and attract anopheles breeding. When humans inhabit these regions with topographic characteristics favourable for anopheles breeding, there is a higher probability of increased human–vector contact and malaria infection in turn.

In regions with differing topographic characteristics, populations can also have differing immunities, such that microclimate that occur in the locations with diverse topographic features influence anopheles breeding. These populations inhabiting these areas are

susceptible to unstable malaria transmission - epidemic attacks unlike in areas with more uniform topography where populations are uniformly exposed.

Studies examining the relationship between topographic characteristics and malaria/mosquitoes have derived elevation from topographic maps (Balls *et al.*, 2004; Cohen *et al.*, 2010); the 90m \times 90m spatial resolution global coverage of Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) (Nmor *et al.*, 2013); the 30m \times 30m Advanced Space-borne Thermal Emission Reflection radiometer (ASTER) Global DEM (Nmor *et al.*, 2013); or during GPS mapping surveys alongside aspect, slope, land curvature, topographic wetness and topographic position indices.

Amongst these topographic characteristics, elevation has appeared often as a governing factor in the regionalisation of the disease, particularly in East Africa, which is characterised by high elevational ranges (Omumbo *et al.*, 2005), as well as studies conducted outside East Africa at broad national scales where changes in elevation are obvious. The impacts of elevation alongside other topographic characteristics form the main points to be discussed in the subsequent sections.

3.3.3.1 Elevation

Elevation describes altitudinal heights which have consequences for the downward flow of water, drawn by gravity, collecting in areas of lower elevation such as valleys and flatlands (Moore *et al.*, 1993; Nmor *et al.*, 2013).

A number of studies in urban or rural areas, such as those of Balls *et al.* (2004), Ernst *et al.* (2006) and Zhou *et al.* (2007), have consistently shown that normally a significant inverse relationship exists between elevation, anopheles presence and malaria transmission, even though this is not always linear. Across the literature, what has been inconsistent is at what height of elevation malaria transmission stops.

Zhou *et al.* (2007), in a multivariate analysis with other environmental variables, investigated the relationship between elevation and abundance of larval habitats as well as adult anopheles. Zhou *et al.* (2007) report a significant and inverse relationship between elevation and anopheles density and abundance of habitat, which ceased above an elevation of 1470m. Similarly, Balls *et al.* (2004) found an inverse relationship between elevation at every 50m and parasite infection in children, from as low as 300m up to 1650m. Other evidence from Lindsay and Martens (1998) suggest cut offs for disease transmission at 1500m for the highlands of Africa and 1800m for the Congo

basin (Snow and Gilles, 2002). However, studies by Ernst *et al.* (2006) contend that at local scales malaria transmission can occur at any elevation, even above 1900m, and under such circumstances change in elevation becomes more important than elevation itself. These studies have revealed the potential impact elevation has on malaria in highland areas, ranging from as low as 300m up to over 1900m and at broad spatial scales in both urban and rural locations, as suggested by Drakeley *et al.* (2005).

In lowland areas or at small spatial scales, there is less experience of the impact of elevation on malaria transmission, owing to the almost flat land surface that exposes populations equally. A study by Myers *et al.* (2009) in small-sized villages in Papua New Guinea examined the impact of elevation in lowland settings where elevation ranges between 67m and 132m. Findings revealed a non-significant relationship between malaria risk and elevation but a significant relationship for every 10m change in elevation. On the other hand, Dambach *et al.*'s (2012) study in a peri-urban region, with elevations between 200m and 295m, recorded a significant increase in the number of anopheles ponds with 100m change in elevation. It can be argued that even though the presence of breeding sites and malaria transmission may decrease with increased elevation, at small scales and in lowland areas, the impact of elevation is minimal and inconsistent. The suggestions put forward by Cohen *et al.* (2008) are directed towards the considering alternative topographically derived features, such as slope and curvature, to assess malaria transmission patterns at small spatial scales.

Though elevation has appeared more frequently in assessing the relation between topography and malaria transmission, other characteristics such as aspect, curvature, topographic wetness and slope have also been considered, particularly in studies at small spatial scales.

3.3.3.2 Slope

Slope is a measure of change in elevation over a certain distance and has been described by Warren *et al.* (2004) to have a strong influence on overland subsurface flow velocity and accumulation of water. The relationship between slope and malaria across the literature has been reportedly inconsistent. Cohen *et al.* (2010) findings suggest the correlation between slope and malaria is a highly significant one because of the way it influences water flow and water accumulation such that steep slopes have a lower tendency to retain water ponds for anopheles breeding. Similarly, Nmor *et al.* (2013) report a significant negative relationship between slope and larval habitat availability in

both univariate and multivariate analysis study. However, Balls *et al.* 's (2004) study, on the other hand, reveals a lack of association between steepness and the presence of the malaria parasite in humans. In contrast, Zeilhofer *et al.* (2007) argue that anopheles mosquitoes make their habitats in shallow slopes that allow water accumulation such that their larval population are undisturbed by flow velocity, and as such should lead to high anopheles densities and, in turn, malaria. It can be argued that anopheles are attracted to where humans live, but humans are unlikely to inhabit steep areas in highland regions, but rather prefer shallow slopes which coincide with vector habitats and, in turn, increase vector–human contact, which will likely translate to disease. Without disagreeing with the impact of slope on vector abundance and disease, Balls *et al.* (2004) suggest, though, that such a measure will be more appropriately applied at small spatial scales or in lowland rather than highland areas where elevation is not a limiting factor. While these are plausible explanations, we should not forget that humans can create buffers such as the use of ITN, so that the increased presence of anopheles mosquitoes does not automatically translate to the occurrence of malaria.

3.3.3.3 Aspect

Aspect of a land surface, as defined by Nmor *et al.* (2013), is the orientation that the slope faces such that it determines the amount of sunlight a site receives, which, according to Chaves and Koenraadt (2010), has consequences for mosquito larval survival. Studies that have applied aspect in predicting anopheles distribution or malaria transmission risks have presented inconsistent results. Moss *et al.* (2011) report the lack of significance between the topographic aspect and malaria in a household survey in Zambia. Similarly, when related to prediction of anopheles habitat, Nmor *et al.* 's (2013) findings also exhibit a non-significant relationship, using the 90m resolution SRTM DEM data and a significant relationship using the 30m ASTER Global DEM. These inconsistent relationships are explained by Clennon *et al.* 's (2010) demonstration on the quality of data used to derive aspect and its predictive abilities. While aspect derived from the 90m resolution SRTM DEM data portrayed a significant relationship with the presence of water as an anopheles habitat, aspect derived from the 30m ASTER Global DEM did not present any significant relationship with the presence of water. Empirical evidence suggests that the true spatial resolution of the ASTER Global DEM is poorer than 30m and the DEM has serious artefacts that have an erroneous effect on any topographic measure derived from it.

3.3.3.4 Topographic Wetness Index

The Topographic Wetness Index (TWI), according to Cohen *et al.* (2010), is an indicator of potential moisture, i.e. an estimate of predicted water accumulation in a defined area, assuming there is surface homogeneity of soil and vegetation. The TWI is an appealing measure because it represents a simple, biologically meaningful description of how topographic characteristics, like slope and surface curvature, may affect malaria risk via suitability for mosquito breeding. TWI is increasingly applied in malaria risk or anopheles mosquito densities relationship studies that are subsequently discussed.

In Nmor *et al.*'s (2013) study in a highland area to predict anopheles habitats, a positive and significant relationship was exhibited between TWI and abundance of larvae natural habitats in both univariate and multivariate analysis. Likewise, Cohen *et al.* (2008) argues that at small spatial scales in highland areas, TWI predicts the presence of human malaria parasite better than other environmental variables. Balls *et al.* (2004) suggest that this index of flow accumulation is only significant when applied side by side with other topographic indices such as elevation. It can be argued that though TWI is an important variable at small spatial scales, such as urban areas, but is only effective when elevation is prevailing as well as where surface cover is homogenous.

3.3.3.5 Topographic Position Index

The Topographic Position Index (TPI), according to Moss *et al.* (2011), classifies the landscape by slope position and landform type (plain, valley, ridge), and represents the difference between the elevation at a point and the elevations of neighbourhood cells. TPI values range from ~ -1 to $\sim +1$ where negative values indicate valley floors and positive values signify hilltops and ridges (Clennon *et al.*, 2010), while values near zero are typical of flat or mid-slope locations. These biophysical attributes are key predictors of habitat suitability, community composition and species distribution and abundance as they correlate conspicuously with many landscape's physical and biological processes. A number of studies have examined TPI in relation to malaria or anopheles characteristics (Clennon *et al.*, 2010; Moss *et al.*, 2011; Nmor *et al.*, 2013). In all these studies TPI has consistently and significantly been related to the vector presence, the disease or the prediction of its habitat. While a prominent variable, Nmor *et al.* (2013) argue that TWI is principally more relevant in diverse highland terrain with topographic conditions characterised by hilltops, valley floors, exposed ridges, flat plains, upper or

lower slopes, and as such not widely applicable to many urban areas like my study location.

3.3.3.6 Curvature

Curvature is the second derivative of elevation and is a measure of rate of change of a slope per unit distance which may affect the stability of the aquatic habitat. According to Mushinzimana *et al.* (2006), it measures the convexity or concavity of the land surface and is an indicator for the possible accumulation of water. It represents the amount by which landscape topography deviates from being flat or straight.

The impact of curvature has been studied more in relation to the anopheles than to the disease. Mushinzimana *et al.* (2006) and Nmor *et al.* (2013) findings report a negative significant relationship while using curvature to predict the presence of larval aquatic habitat. On the other hand, Balls *et al.* (2004) did not find any significant relationship between curvature and human malaria. From the evidence accrued, it can be argued that curvature is a plausible predictor of the presence of water-based larval habitats, but while predicting malaria, behavioural and confounding factors may produce a non-significant relationship with the disease itself.

Summary evidence from the literature has demonstrated the ability of various simple to complex topographic derivatives to predict the presence of larval habitats as well as the transmission patterns of malaria over spatial scales and landscape features. Out of all the commonly applied variables, elevation has been most consistent in its relationship. However, in lowland areas or at small spatial scales such as urban areas, a multiple of variables apply, owing to heterogeneous surface characteristics as explained earlier for example soil and vegetation types. In respect of this, Cohen (2008, 2010) argues that a topographic variable derived from multiple topographic characteristics gives a better prediction because, apart from considering elevation, it considers the shape of the earth and landform variability. Cohen (2008) recommends alternative variables where elevation differences between households are minimal but local variability in landform is experienced.

This thesis will examine two important topographic variables (elevation and slope) in relation to the disease risk in Lagos state, as examined and found to be relevant by Drakeley *et al.* (2005) and Myers *et al.* (2009) in urban and lowland settings respectively. Other topographic variables such as TWI, TPI, aspect and curvature, though found important in the literature reviewed, are not applicable in areas

characterised by multiple land-use types and lacking diverse topographic features. Through this study, my research will contribute to knowledge on the influence of this geographic feature in disease risk in heterogeneous lowland urban areas.

3.4 Built Environment

The built environment consists of that part of the habitat manipulated by humans for their daily activities and goals, including living, working and social events, which can have a consequence for health. According to Roof and Oleru (2008) and Meade and Emch (2010), what we modify extends from building types, housing patterns and household environments, settlement types, working environments that include agriculture types and availability and accessibility to health services as well as social spaces for human wellbeing.

3.4.1 Agriculture

In urban areas, there is an increasing promulgation of agricultural practices consisting of irrigated and non-irrigated single/mixed farming activities and animal husbandry (Baumgartner and Belevi, 2001). According to Fournet *et al.* (2010) the last decade has seen these brought into urban areas of Sub-Saharan Africa by rural migrants maintaining their practices and livelihoods; community initiatives set up to curb unemployment making its residents expand agriculture across city centres into the peripheral belts. While this combats malnutrition and increases food security for the urban poor, it creates optimal vector breeding conditions and increased malaria risk, which many urban governments do not recognise (Baumgartner and Belevi, 2001).

Agriculture is one of the LULC types reported by a number of authors to have the strongest positive association with malaria intensity over other types of LULC in urban areas (Afrane *et al.*, 2004; Klinkenberg *et al.*, 2005). In particular, irrigated farmlands such as rice paddies, vegetable and maize farms are typical environments that are known to encourage vector breeding and resting in both the wet and the dry season (Klinkenberg *et al.*, 2005; Matthys *et al.*, 2006a). Through these activities, trenches are created for the formation of shallow water to irrigate seed beds and, in one study in Abidjan, Cote d'Ivoire, over half of the trenches were breeding sites for anopheles larvae (Matthys *et al.*, 2010). Other agricultural breeding sites in urban areas include

irrigation wells, non-cemented wells, fadamas¹², ditches for furrow systems and human footprints (Dongus *et al.*, 2009; Machault *et al.*, 2009; Machault *et al.*, 2010).

Apart from farming practices, animal husbandry can also present situations where the anopheles mosquito becomes either animal or human blood-dependent (Keating *et al.*, 2005; Deressa *et al.*, 2007; Peters, 2010). In this respect, Peters (2010) states that at such a scale, for animal husbandry activities, the greater the number of animals present in an area then the more alternative blood sources available for the anopheles and, in turn, the lower the incidence of malaria in humans.

The abundance of these agricultural-type habitats is often translated to increased abundance of the vector and, in turn, the disease. As such, households living in close proximity to agricultural lands are likely to be faced with increased malaria intensity. Numerous studies have established a relational link between proximity to urban agriculture (farming practices) and malaria. Findings have been consistent. Afrane *et al.* (2004) and Yadouléton *et al.* (2010) household scale approach and Klinkenberg *et al.* (2005) paediatric study examined the relationship between malaria parasite presence and proximity to irrigated land and vegetable farming in an urban location, and the key findings shows this was significantly associated with increased malaria risks in households. The consistency of results suggests that proximity to urban agricultural sites increases risks to malaria in households.

3.4.2 Housing Characteristics

“Housing” is that part of the built environment whose characteristics reflects our cultural, social, age and economic lifestyles. It is such places that Sargent and Johnson (1996); Gatrell and Elliott (2009) and Meade and Emch (2010) describe as a manifestation of human’s overall behaviour such that they have a locational and socially constructed meanings for us. Across the literature I note that there is no gold-standard measure of housing characteristics.

A range of housing characteristics have represented a socio-economic indicator, or a risk variable through the way they can influence entry into houses by mosquitoes or sustain them indoors. Indoors housing design and types of structures determine microclimate conditions that cause change in room temperature and humidity, thereby influencing indoor conditions for anopheles to remain, and in fact to breed. Commonly

¹² Hausa name for low lying plains underlain by shallow aquifers found along major river systems.

studied housing characteristics in malaria risk literature can be grouped into: those associated with the physical structure of the building, those associated with the building environment, here called homestead, and those pertaining to the inhabitants of buildings and homesteads such as humans and animals.

Housing characteristics associated with the building include house type, design, roof, wall and window materials, presence/condition of window and door, mosquito screens, eaves, electricity and building materials (Ghebreyesus *et al.*, 2000; Wang *et al.*, 2006a; Yé *et al.*, 2006; Yamamoto *et al.*, 2010). Homestead characteristics are presence of animals/livestock, vegetation cover including farms/gardens, water presence, taps, wells and refuse dumps (Adeleke *et al.*, 2008; Yamamoto *et al.*, 2009; Peters, 2010). Others include household size, room density and location of sleeping rooms (Clark *et al.*, 2008; Siri *et al.*, 2010). What matters in different locations have varied and in all, their importance for malaria are inconsistent. What Lindsay *et al.*'s (2002), Kirby *et al.*'s (2008) and Peterson *et al.*'s (2009) studies discussed further on tell us primarily to note are those characteristics that encourage vector entry and sustain their presence in house which have more to do with household's preventative behaviour than socio-economic status.

In Yé *et al.* (2006) and Yamamoto *et al.* (2010) examined the impact of iron roofs on malaria in peri-urban populations both in Burkina Faso and they did not find any significant influence arising from the use of this roof type. Though Yé *et al.* (2006) argue that iron roofs create indoor climate conditions, i.e. higher temperatures, which are not conducive for anopheles survival which is a plausible explanation, a further look into the study population characteristics reveals that the power size for the analysis may have consequences for the generalisation of the findings.

Holes in the wall, eaves, the presence of windows and doors, and the use of window and door screens have been related to malaria and findings are inconsistent. While Ghebreyesus *et al.* (2000) note higher risks with the use of windows, Deressa *et al.* (2007) did not find any statistically significant relation with holes in the wall as well as Peterson *et al.*'s (2009) with use of window screens but Lindsay *et al.* (2002) and Kirby *et al.* (2008) confirm and demonstrate increased vector entry and density with open eaves and lack of mosquito screens. Whether these characteristics are important in all urban areas is a matter of study context, as these can be imperatively economically driven variables, even though Lindsay *et al.* (2002) and Peterson *et al.* (2009)

emphasise their partial contribution from behaviour. Lindsay *et al.* (2002) findings note in their experimental study that well-built houses of the affluent, but built without screens, were more subject to vector entry, and a 12% increase in malaria rates with humans living in them, than less well built houses of poorer people using screens. What this means is that an opportunity or source of mosquito house entry is an important housing variable but its measure will be driven by that which is most important and represents the diversity of the study context.

As urban locations are generally classed as more affluent (Mugisha *et al.*, 2002; Robert *et al.*, 2003), households there, above all, are likely to afford better houses to protect from a number of factors (security, hazards, disease including malaria), built with good-quality materials, walls, have windows, doors, screens, and closed eaves. This can make discrimination of housing characteristics in urban locations using these variables difficult, with consequences for the power of the analysis (Peterson *et al.*, 2009). Most studies often have concentrated on their presence and less on their condition. This study will focus on conditions of housing characteristics that are important for urban locations.

Interestingly, Yamamoto *et al.*'s (2010) study in a paediatric population in semi-urban Burkina Faso found electricity use to be associated with increased malaria risk, as the alternative of biomass fuel burning produces smoke that is thought to deter mosquitoes' entry into houses; possibly, electricity use in better-quality housing would presumably not show this trend. While this study has noted the influence of electricity in an urban location, its applicability will be a matter of local context.

According to Trape *et al.* (1992), spreading an anopheles population over a denser human population tends to reduce the degree of exposure of each person to malaria infection. In univariate settings, findings from Ernst *et al.*' (2006) multitemporal study, Siri *et al.* (2010) and Messina *et al.* (2011) in this respect show that a positive and statistically significant relationship exists between household size and malaria risk. In a multivariate assessment, Siri *et al.* (2010) findings follow the same direction with the univariate analysis results, but Ernst *et al.* (2006) (in most years studied) and Messina *et al.* (2011) report a non-statistically significant status with almost no influence. When assessed overall, I argue that this is an important variable associated with increasing malaria risks, but it may become less important when other factors are integrated in a

population-based study over studies that focus on severe cases of the disease in vulnerable age groups, such as in Siri *et al.* (2010) study.

Ernst *et al.*'s (2009) and Ayele *et al.*'s (2012) studies report that increased room density is a deterrent for increased malaria intensity, leading to reduced biting rates of anopheles per human in a room used for sleeping. However, Carter *et al.* (2000) and Clark *et al.* (2008) dispute this, and suggest higher room density to be positively related to a higher number of malaria cases in the general population. This infers that biting rates are higher in rooms with higher numbers of people; hence, there is some inconsistency regarding room density and malaria risks. In this regard, Dietz *et al.* (1974) and Lacroix *et al.* (2005) demonstrated the increased attractiveness of mosquitoes to humans carrying the parasite, without thereby substantiating Ayele *et al.*'s (2012) findings and study settings, where more people carried the parasite in shared rooms. However when the attraction extends to other rooms, the anopheles may prefer to travel further to seek food, rather than dwelling amongst humans. Even though Clark *et al.*'s (2008) randomised control trial study is considered a more reliable study design, Carter *et al.*'s (2000) and Clark *et al.*'s (2008) studies have both converted continuous data into ordinal ranked classes of room density; as a result, they lose information, which may affect the study results. When related to Trape *et al.*'s (1992) demonstrative study, this evidence points to decreasing influence of the variable. However, more experimental studies are needed to confirm this.

3.4.3 Homestead Characteristics

“Homestead” is defined as a building and its area of land with other outbuildings in African rural settings, including livestock sheds, drainage, water points (Oxford English Dictionary). As this description fits many African urban settings, I use it here to describe housing environments which humans interact with in a number of ways.

In urban areas, they cultivate gardens/farmlands within their homestead or as an external plot in poorer households; they partake in animal husbandry and keep domestic pets such as dogs and cats within their homesteads; in more affluent areas, they beautify their surroundings with flowers and the presence of such vegetation can, for example, create a microclimate condition that typify adequate settling and breeding places for anopheles mosquitoes (de Zeeuw, 2004; Chaves and Koenraadt, 2010). For water supply, households may have external water sources such as wells, or taps and boreholes shared with neighbours; where water shortages occur or the water supply is

irregular, they store water either in open or closed containers. As part of daily human activities, people produce and dispose of waste and refuse, more often than not openly, or in open drains within their homestead environs. Depending on household's socio-economic status, households with shared sanitary facilities situate them outside the buildings for easy shared access. When humans engage with their environment in these ways, there are opportunities to create or prevent focal habitats for anopheles mosquitoes with consequences for the disease.

Numerous studies have examined the relationship between malaria and the features that characterise homesteads as described earlier, such as the presence of wells, gardens, farms, livestock and domestic animals, water storage containers, open drains, stagnant water, refuse and waste water disposal points. While some associations have been significant, others have produced inconsistent results. The findings are discussed subsequently.

Ye *et al.* (2008) report a positive relationship between forms of vegetation (farmland, gardens, flowers, and grasses) in households' living environments and malaria infection in a paediatric population situated in Nouna, a peri-urban area in Burkina Faso. Githinji *et al.*'s (2009) and Peterson *et al.* (2009) findings are similar in this respect. Githinji *et al.*'s (2009) however state the moderating impact of the presence of livestock feeding on them with consequences for the reduced abundance of vegetation. In this regard, Peterson *et al.* (2009) argue that irrespective of the abundance of vegetation within homesteads, what are most important, are the outdoor and preventative behaviours employed by households.

Keeping domestic animals in homesteads has promoted differing malaria infection states in populations because of the zoophilic feeding tendencies displayed by the anopheles mosquito species under certain conditions (Yamamoto *et al.*, 2009; Peters, 2010). Yamamoto *et al.* (2009) and Temu *et al.* (2012) found a significant positive relationship between the presence of livestock types (donkeys, pigs and rabbit) and malaria infection but not with others (poultry, cattle, sheep and goats). On the other hand, Peters (2010) reported a significant negative relationship between malaria transmission and keeping cattle in India as well as Kibret *et al.* (2010) who uses a household scale approach and the presence of a range of bovines, ovines and equines (cattle, sheep; goats, ram, horse and donkeys) though findings from Kibret *et al.* (2010) study is not statistically significant. These findings are inconclusive and may be

attributed to the risk variable been highly influenced by behavioural attributes interacting with the built environment. In this case, Peterson *et al.* (2009), Kibret *et al.* (2010) and Peters (2010)¹³ offer some explanation. First, livestock may live in separate enclosures even though they are still within the homestead; second the proximity of the livestock to humans; third, the presence of alternative blood sources which are greater in number, and lastly the type of livestock which results in differing malaria metric indices in humans.

The presence of water in many forms is an important habitat for anopheles because it sustains their breeding and longevity (Adeleke *et al.*, 2008). Thus the condition of the homestead with respect to collected and standing water, such as running taps, wells, puddles of water, moist garbage sites, domestic containers, and drains as habitats for the anopheles, can become risk factors for malaria in humans (Okogun *et al.*, 2003; Adeleke *et al.*, 2008; Olayemi *et al.*, 2011). Consistently, their presence has had consequences for increased malaria risks, as shown in studies by Yamamoto *et al.* (2010) and Ayele *et al.* (2012). However, Peterson *et al.* (2009) found that taps in closer proximity to households decreased malaria risks. Peterson *et al.* (2009) finding is at variance. Though not explicitly stated, it can be explained that in Peterson *et al.* (2009) study, the presence of a running tap in the homestead is likely to be an indicator of socio-economic status rather than a direct risk factor. This is an important factor for urban location because where dilapidation of infrastructure that includes broken pipes and irregular water supply occur, it creates temporary habitats.

Another study by Ghebreyesus *et al.* (2000) reports a non-significant relationship between the presence of a well in a homestead and increased risk of malaria, Srivastava *et al.* (2001) study argues that wells only become significant by season i.e when they are disused in the dry season it then has the opportunity to harbour mosquitoes which will then translate to increased biting rates and possibly malaria in that season alone and not in the wet season when the well is in use. While the impact of the variable is inconclusive, Adeleke *et al.* (2008) entomological study report wells as efficient breeding habitats for anopheles mosquitoes in urban areas.

3.4.4 Access to Health Services

Two types of access to health services have been noted across the geography of malaria literature and Nigeria: social access concerning monetary affordability and

¹³ Peters (2010) study is discussed further under ethnicity, religion and culture subsection.

relationships, and physical access relating to distance/proximity and ease of travel to a health care facility (Egunjiobi, 1983; Baume *et al.*, 2000; Mugisha *et al.*, 2002; Noor *et al.*, 2006). In all, what I note is that they are variables associated with progress from mild malaria to severe malaria or that may lead to consequences such as mortality or disability (Baume *et al.*, 2000; Saeed and Ahmed, 2003b). While these are important, they are beyond the scope of this research, which focuses on mild malaria and thus are not discussed further.

The significance of agricultural lands in increasing malaria transmission risks in urban areas has been established from the earlier studies as an important variable to be considered in understanding the ecology of urban malaria. This is also true for housing and homesteads, but what constitutes these characteristics is determined by the locality of the study. This thesis will therefore translate the importance of these range of variables and examine their relevance to malaria infection in a large urban centre of Lagos, as carried out similarly in smaller urban locations by Afrane *et al.* (2004), Klinkenberg *et al.* (2005), Ye *et al.* (2008), Peterson *et al.* (2009) and Alemu *et al.* (2011), and through this, construct meanings for geometric space and human importance of place.

3.5 Socio-cultural Environment (Behaviour)

Behaviour, as described earlier, is a manifestation of multiple elements: education, culture, religion, knowledge, socio-economic status, migration, ethnicity, and occupation associated with the socio-cultural environment and interact with physical and built environment in ways that promote or discourage vector-human contact. In malaria literature, variables such as ethnicity, occupation or education are often used as a proxy measure of socio-economic status instead of income or wealth. In this review, I attempt to separate them as individual variables even though there are often overlaps.

3.5.1 Ethnicity, Religion and Culture

Ethnicity, religion and cultural practice combine to often influence the way in which people interact with the environment. Brown *et al.* (1996) describe culture as a primary mechanism for human survival and this manifests itself in behaviours influenced by the belief mechanism. They can cause humans to interact with the landscapes such that this creates knowledge that is made manifest in settlement and agricultural patterns as well as protective behaviours. Phillips *et al.* (2009) and Peters (2010) propose that ethnicity, religion and culture are important factors in the spatial and social patterning of the

malaria. Across the literature, studies have examined practices stemming from them, historical immunities developed/possessed and the fact that certain ethnic or religious groups are more affluent than others. Other studies have examined ethnic groups without stating aspects being considered. The studies have directly or indirectly examined these relationships using both qualitative and quantitative methods. This review focuses on direct relationship studies and the key findings are discussed.

Panvisavas's (2001) mixed methods study examined behaviours deriving from different ethnic groups in the choice of where to live and their livelihoods and its consequences for malaria risks on the Thai–Myanmar border. The findings showed that there are differences in the malaria risks amongst ethnic communities and class lines centred on a lifestyle and compromised by poverty. Non Thais ethnic group prefer to live in forests, a simple agrarian lifestyle that could not fit into the town and are poorer while the Thais ethnic group prefer to live in the towns and are more affluent. Forests are a major breeding ground for mosquitoes and the non-Thai's live in their close proximity in addition to the fact their residences are not officially registered due to its in accessible location in the forests put them at greater risk of malaria (568 per 1000 persons) over the Thais (204.7 per 1000 persons) who live in registered houses in town that are away from forests and their place of residence additionally gives them access to malaria intervention schemes. Findings from Thang *et al.* (2008) quantitative study in peri-urban Vietnam are similar. Ethnicity was an important variable for higher malaria risks with the forest way of life of the Ra-glai ethnic group that compromises for higher malaria risks (15%) in the ethnic group over others (6%). This "location of residence" attribute puts certain ethnic groups at greater risk of malaria over others.

Phillips *et al.* (2009) and Achidi *et al.* (2012) demonstrate the significant link between ethnicity and malaria based on historical immunity and differences in susceptibility. In the Phillips *et al.* (2009) study examined holiday makers to malaria endemic countries of different ethnicities, ethnicity was defined as black (black African and black Afro-Caribbean), Asian (from South Asia, specifically, India, Pakistan, Sri Lanka, and Afghanistan), and white. The key findings showed that whites had the highest risk of severe malaria while blacks had the lowest risk and this arose because the blacks have had previous exposure and clinical attack from malaria and have developed some historical immunity over the adults not coming from malaria-endemic countries thus putting them at lower risks.

Findings from other comparable studies by Modiano *et al.* (2001); Achidi *et al.* (2012) and Tiono *et al.* (2013) found genetically significant protection from severe malaria in Fulani ethnic groups but in Ye *et al.*'s (2008) study the Fulani ethnic group did not present any significance. Similarly, Hustache *et al.* (2007) study identified immunogenetic backgrounds and generational ethnic mixing in French Guiana as a protection from malaria incidence over other ethnic groups. Ye *et al.*'s (2008) study does not link ethnicity to any genetically related risk factor but rather examines its incidence in the population without stating the dimensions of ethnicity being examined.

Peters (2010)'s study describes how religion, ethnicity and culture intertwine to influence spatial patterning in disease risks. Peters (2010) suggests that the spatial patterning of malaria arises from the way ethnic and religious practices determine agricultural activities. In this study, the regions inhabited mainly by the Hindu Tamil ethnic and religious group have an almost malaria-free zone owing to their religious attachment to cows, which they consider to be holy and thus keep a large number of them. These cows, even under suitable ecological characteristics that favour the sustenance and development of vectors and parasites, have provided an alternative blood source for the anopheles mosquitoes. Similarly, in the same study, areas inhabited mainly by Muslim Moors have recorded the absolute minimum of malaria incidence because they have a high proportion of Muslim inhabitants who raise goats in large numbers. This, though, contradicts earlier discussion (see section on animal presence under homestead characteristics) that present significant increased risks of malaria where livestock are tethered within the homestead. According to Peters (2010)'s study, it can be argued that while the Hindu Tamils and Muslim Moors take this as a religious way of life such that they rear them in large numbers, in other studies like Peterson *et al.* (2009) (as discussed earlier as animal presence under homestead characteristics), animals and livestock are taken as a subsistence economic activity often practised by the urban poor. One thing can be learned from this: numbers matter. Where animals are present in greater numbers than humans, there is the likelihood for mosquitoes to manifest their zoophilic tendencies, and vice versa with its impact being modulated by the predominant mosquito specie type in that location (Service and Townson, 2002).

In summary, ethnicity, culture and religion have different dimensions which when examined individually present a number of implications for malaria. Oresanya *et al.* (2008) study in Nigeria though not examining malaria risks but rather uptake and use of

insecticide treated nets (ITN) and religion found ITN usage was three times higher in Christians than in Muslims which could translate to differing malaria risk from these behaviours presented by the religious groups. In Okwa (2003) study in Lagos, Nigeria, the percentage of infection was higher in Christian than Muslim pregnant women and Christians still had higher percentage of non-infected persons but no explanation was given to explain this pattern. There is a challenge in comparing these studies because of multidimensionality of the risk variables and the fact that studies reviewed focuses on a different dimension. However, as a first step, it is important to explore these risk factors given the multicultural nature of Lagos state to pave a way for a better understanding of its role.

3.5.2 *Economic Status*

Malaria is frequently referred to as a disease of the poor or a disease of poverty (Sachs and Malaney, 2002). A perusal of the global regionalisation of the disease is sufficient evidence of this claim, given the concentration of malaria in the world's poorest continents and countries. At other scales, this evidence may be inconsistent and more may be needed to avoid ecological fallacy.

There are a number of measures representing economic status: income, expenditure and asset ownership, and other correlated proxy measures like gender, urban/rural location, education and occupation. Gender, according to Worrall *et al.* (2003) is sometimes used as a proxy for SES reflecting the social and material disadvantage experienced by women in many parts of the world. However gender is less commonly used in malaria studies. Here we focus on those frequently occurring in the malaria literature where their relationship with malaria is purely an economic one: income, expenditure and asset ownership. Across these three, there are still inconsistencies in their measures such that a challenge is faced in comparing studies.

Though income and expenditure are a more generally accepted gold standard to represent household economic welfare (Worrall *et al.*, 2003), it is often difficult to obtain accurate financial data from respondents in developing countries. According to Deaton (1997) and Rutstein and Johnson (2004), this is for a number of reasons: people's lack of knowledge about exact finances, multiple earners and spenders in households, and unwillingness to disclose unbiased financial data for several reasons. In addition, collecting detailed income or expenditure information is prohibitively time-

consuming and costly, and results may be influenced by seasonality in income flows (Rutstein and Johnson 2004). Thus, most studies have used asset ownership, which, according to Filmer and Pritchett (2001) and Rutstein and Johnson (2004), represents a more permanent way of assessing household economic status and requires only a single respondent and fewer questions compared to the income and expenditure. Filmer and Pritchett (2001) demonstrated comparable results in applying both expenditure and asset-based approaches in a school enrolment study. However, what constitutes applicable assets has varied from study to study and between rural and urban locations.

In malaria literature, assets have generally constituted either one or a selection of over 20 household items, housing characteristics, water and sanitation facilities and access to services (Filmer and Pritchett, 2001; Vyas and Lilani, 2006). The assets used have varied within rural areas or across rural and urban areas. In rural areas, common assets include radios, livestock, beds and bicycles, while housing characteristics are walls, roof materials, water and sanitation facilities including toilet characteristics, types of water source and cooking amenities, and access to health care services (Deressa *et al.*, 2007; Ernst *et al.*, 2009; Ayele *et al.*, 2012). In urban areas, ownership of a vehicle has featured prominently, in addition to some assets mentioned earlier, such as livestock and radios (Yamamoto *et al.*, 2010). Often these selections are based on face validity. Rutstein and Johnson (2004) suggest the following broad categories of assets: water supply, type of vehicle, sanitation facilities, persons per sleeping room, electricity, ownership of agricultural land, radio, domestic servant, television, type of flooring, refrigerator and telephone. A full list of assets is suggested in the demographic and health survey (DHS) reports, which often many of the studies conducting similar surveys select from to relate to malaria risks. The majority of the malaria risk studies adopt an asset-based approach to measure economic status. This asset-based approach provides a value/class that measures wealth. Filmer (2005) used asset ownership data collected in DHS surveys to examine socio-economic differences in malaria risks. A potential problem with the asset index approach is differences in the assets used across surveys and studies; even those studies which use a common asset index cannot be readily compared, except insofar as they provide a relative measure of poverty.

For the purposes of analysis and interpretation, households are frequently divided into equal-sized groups (four or five quartiles or quintiles) according to their level of asset ownership by applying a weight derived using principal components analysis (Vyas and

Lilani 2006) or a summation of number of assets owned (Yamamoto *et al.*, 2010). Often the actual distribution of the underlying index value is rarely reported, unknown and most often taken on face validity. For example, the distribution may be extremely uneven, with a large portion of the population having very few assets, and a very small proportion having a large number or not using the appropriate assets suitable for their ecological setting. As such, Rutstein and Johnson (2004) suggest the inclusion of country-specific items with rural and urban considerations; however, this still presents the difficulty of cross-country comparisons and makes the justification for the division of the asset index into four or five equal parts unclear.

In the malaria studies reviewed, most have applied an asset-based approach and others have examined the relationship between income and malaria risks. In these studies, assumptions apply for choosing the particular method as well as the problems identified earlier with using any of the approaches, and are often not explicitly stated; neither is their methodologies fully described. For example, in Saeed and Ahmed's (2003a) determinants of malaria risk study, the percentage of income spent on food expenditure was applied to a refugee camp population in Sudan. Even though not overtly stated, asset ownership is not an appropriate method to describe the economic status of households under such transitory conditions. Thus, while reviewing these studies, it is important to bear in mind that inconsistent methodologies are often employed, making it difficult to draw final comparisons across the literature, even though the studies have often drawn different conclusions about the relationship between economic status and malaria at differing spatial scales.

On a global scale, Sachs and Malaney (2002) demonstrate a significant inverse relationship with a country's malaria endemicity and its per capita GDP, arguing that malaria causes underdevelopment and underdevelopment brings about malaria. Therefore, malaria is a double-edged sword. Historical evidence backs this causal pathway. Nájera (1994), in this respect, argues that the disappearance of malaria in parts of Europe was associated with economic development related to agricultural expansion, rather than interventions such as vector control or chemoprophylaxis. It is argued that the lack of success to combat malaria is economically driven by a country's purchasing power and ability to influence global politics, such that malaria's regionalisation is yet limited to poor developing countries without the ability to negotiate global politics.

At a local scale, findings are mixed. Findings by Deressa *et al.* (2007) and Ernst *et al.* (2009) in Ethiopia and Kenya respectively reveal that malaria risks seem to affect multiple wealth classes – the poor, less poor and wealthy – approximately equally. In an urban area study, Yamamoto *et al.*'s (2010) results echo similar findings. On the other hand, Baragatti *et al.* (2009) and Klinkenberg *et al.* (2005), in other urban studies, found a significant inverse relationship between asset ownership and malaria, while in Saeed and Ahmed (2003a), an income and food expenditure approach to examine malaria risk levels revealed that households where more than 25% of income was expended on food were at higher risk of malaria, while those with no income had no significant relationship with malaria risk. In Ghebreyesus *et al.*'s (2000) study, malaria was not significantly associated with wealth assets such as radios, livestock or sources of water, but significantly associated with the number of sleeping rooms and ownership of a separate kitchen. It is obvious that the findings are inconclusive, with some reasons attributable to earlier concerns on methodological rigour. In addition, at the multiple levels, the direct link between malaria and wealth may be flawed owing to intervening knowledge, attitude and practice factors that are not concerned with wealth but behaviours, and these, together with the built environment (Lindsay *et al.*, 2002), can put households at risk irrespective of their economic status.

In urban areas heterogeneity in economic status often exists, as confirmed in Klinkenberg *et al.*'s (2005) and Baragatti *et al.*'s (2009) studies. This variable will be applied in Lagos state to understand its influence on the spatial patterning of disease.

3.5.3 Level of Education

Education as a variable in epidemiological studies attempts to capture the knowledge-related assets of a person so that it may be related to the significance of a health outcome. It can be measured as a continuous variable (years of completed education), or as a categorical variable by assessing educational milestones such as completion of primary or high school, or higher education diplomas or degrees (Galobardes *et al.*, 2006). The idea behind the continuous measure is such that the time spent in education is considered to be of greater importance than educational achievements, on the basis that every year of education contributes similarly; the categorical measure assumes that specific achievements are important in determining status. However, in developing countries, this is not always the case with the continuous measure, where lack of finance could lead to absenteeism in school, particularly at exam times, with consequences for

repetition of classes and a higher number of school years that may not translate to increased knowledge. Education is also applied as a generic measure to construct socio-economic status and sometimes related to level of knowledge displayed about malaria even though this correlation often does not exist. In this case, however, the focus is its relationship with malaria risks as an individual variable.

Its association with malaria generally is manifold. As education reflects intellectuality, knowledge attained through education may affect a person's cognitive functioning (Galobardes *et al.*, 2006) and shape not only this behaviour but the behaviour of the whole household in a way that it has various consequences for the risks of malaria within that household. According to Galobardes *et al.* (2006), education also captures the transition from childhood to adulthood and thus can be a strong determinant of future employment and income with impact on the resources available in a household to influence the risks to malaria.

Just as there is no standard measure of household economic welfare in malaria studies, in the body of knowledge examining the relationship between malaria risks and education, a standard measure of educational achievement is also lacking. This lack of a standard measure makes it difficult to judge or draw blanket conclusions, owing to differences in study focus or the classifications for level of education applied in each study. Frequently, level of education is categorised to include low and high; illiterate and literate; none, primary, secondary and above; primary school or none, secondary school or higher; illiterate, literate, primary, middle, high school and above; none, primary, secondary, tertiary, non-formal (Njama *et al.*, 2003; Thang *et al.*, 2008; Ernst *et al.*, 2009; Phillips *et al.*, 2009; Aina *et al.*, 2013). Little is known of what defines the cut-offs for some categories such as low and high, illiterate and literate; the studies lack explanation to this effect. Some studies on the other hand, have used the number of completed years of schooling (Baragatti *et al.*, 2009). In addition, information on the level of education has been requested from either the respondent where the study focused on the general population; the caregiver or head of household. These irregularities in measures as well as study focus make it problematic to compare findings across studies.

Numerous studies have examined the relationship between malaria incidence and education, and inconsistencies exist. In Ernst *et al.*'s (2009) study, malaria was significantly associated with education for all classes of educational achievement.

Similarly, Saeed and Ahmed's (2003) and Baragatti's (2009) findings reveal a significant relationship between the two, irrespective of the classification of education levels and age categories of the study population. In another study, however, contrary results are recorded. In Parajuli and Ghimire's (2010) study, the level of education was not significantly related to the risk to malaria, in fact, the literate population in this study was at a higher risk of malaria than the illiterate population, which is inconsistent with earlier studies. Similarly, in Njama *et al.*'s (2003) study in an urban area, education of caregivers was not significantly related to occurrence of childhood malaria. Njama *et al.* (2003) state that even though the variable was not significant, the caregivers displayed high levels of knowledge about the disease, home management practices and treatment-seeking behaviours, which could often be correlated with education. Koram *et al.*'s (1995) study in peri-urban Gambia suggests, though, that many cases of malaria develop to severe malaria in children due to the lack of education and knowledge on the part of the caregiver. Thus, under severe malaria conditions, education and knowledge are important factors that influence progression of the disease from mild to severe. In this respect, the characteristics of the study population can influence the direction of the relationship between these variables; but they are important variables to be examined in relation to the risks of infection in urban areas.

3.5.4 Occupation

Occupation is a reflection of a person's place in society related to income, education, and less often, working environment characteristics. In many instances, level of education is not always a direct predictor of the type of occupation undertaken by people, particularly in circumstances where unemployment and underemployment are high. According to Galobardes *et al.* (2006), occupation measures are in some sense transferable. For instance, the occupation of the head of household or the highest status occupation in a household can be used as an indicator of the socio-economic status of dependants (for example, spouse and children) or the household as a unit. While occupation type can offer more benefits for health such as privileged access to health care coverage, it may also reflect the environmental exposures both individuals and household members face.

Just as standard of measures of education and economic status are problematic, so also is occupation. Though there is an International Standard Classification of Occupations (ISCO), ISCO-08 (International Labour Office, 2007), many national occupation

classifications are adapted from this, and often what constitutes an occupation class differs from location to location, making comparisons difficult. Some categories of people also are difficult to classify under an occupation: for example, the unemployed, the retired, housewives, students, volunteers, those working in informal sectors or undertaking illegal jobs, or the self-employed. Also, certain people also may not want to disclose their occupation (e.g. occupations in secret service). For these classes of people, fitting them into an occupation class may prove problematic; such difficulties are not reported in many studies.

In the malaria literature, occupation classification has varied, with no two studies having any similarities with regards to occupational classes. However, what we can take from the studies is that certain occupations expose persons to higher risk of vector-human contact, with consequences for increased malaria transmission.

Many authors have explored the relationship between malaria risks and various occupational categories, and under diverse conditions the findings have varied. Agricultural workers, night-watchmen and gem miners are frequently studied owing to the nature of their jobs that coincide with night-time, seasonal, migratory and often require inhabiting temporary and poorly constructed homes in the agricultural farmlands or excavation sites for a given period (Thimasarn *et al.*, 1995; Yapabandara and Curtis, 2004). Even when houses are more permanent or workers are not migratory, clustered settlements develop around work sites in forest locations, which are normally conducive to mosquitoes breeding. Under such conditions, these workers and their households are exposed to infectious mosquito bites and, in turn, higher malaria risks.

Ferreira *et al.* (2012) examined the relationship between malaria and occupational types in Brazil, and there was a 67% higher prevalence of malaria amongst gold miners than other occupational types. Within the gold mining population, 92% of those who worked in mineral extraction had a higher prevalence than those working indoors. This was highest in clustered mining settlements which encouraged increased biting rates within high-density households. Similarly, in Sri Lanka, gem mining creates excavation pits and holes that promote anopheles breeding, and gem miners make their homes without protection that cannot be sprayed owing to their temporary nature. These houses give no protection from the mosquito vector and the gem miners are faced with higher biting rates from mosquitoes (Yapabandara and Curtis, 2004). In the same study by Yapabandara and Curtis (2004), night-watchmen who guard gem pits had higher

malaria prevalence. While these studies have consistently reported the exposure of agricultural and mine workers to malaria, Guthmann *et al.* (2001) report, on the other hand, the protective influence of working on an agricultural farm and living in an agricultural settlement. Guthmann *et al.*'s (2001) finding is, however, not generalisable for a number of reasons. Firstly, the agricultural workers avoided the farms during the peak biting periods of the mosquitoes; secondly, the homes of the agricultural workers are well built with limited entry by mosquitoes. It can be argued that behavioural factors and occupational exposures either create buffers or opportunities for increased incidence of malaria. As stated by Peterson *et al.* (2009) in his study in urban areas, working outdoors puts adults at even higher risk than children, and little is known about such indoor and outdoor environments in urban areas that can feed into intervention programs. Even though agriculture is practised in urban areas, evidence from Klinkenberg *et al.* (2004) (discussed earlier under urban agriculture) shows that residence in close proximity to farmlands is more important than occupation when considering malaria risk. However, certain night-time occupations such as night-watchmen, as studied by Yapabandara and Curtis (2004), are prominent in urban areas, making occupation an important aspect to be investigated; but little is known about its influence other than in rural areas.

This thesis will examine multiple occupations such as night-watchmen and participation in night-time commercial activities, and their exposures in urban areas in relation to the risk of malaria infection. Through investigating this risk factor, the research will further understanding on its role in the ecology of urban malaria.

3.5.5 Knowledge Attitude and Practice (KAP)

With respect to the focus of this thesis, Knowledge Attitude and Practice (KAP) measures the level of knowledge about malaria, the attitude as an expression of favour and disfavour towards the disease, and the behaviours that constitute both preventative, treatment and management practices towards the disease. KAP is often influenced by a person's past or present, and is informed by many socio-cultural aspects of the society (for example cultural, religious, education, occupation and income), sometimes blurring relationships with disease outcomes. Studies on malaria KAP are increasingly being published owing to sub-disciplinary changes that accommodate such research, as indicated in the previous chapter. These studies have sometimes considered KAP as a whole, or one aspect of KAP, for example knowledge, while others have addressed

behaviour and its relationship with malaria. In addition, researches on KAP have addressed it in relation to treatment-seeking and preventative behaviours and socio-economic characteristics, and less often to the incidence of the disease. Evidence from these studies shows that depending on the circumstances individuals can hold several KAP explanations of malaria.

A number of studies in contemporary Africa have shown that malaria transmission routes are often not always understood by communities (Aikins *et al.*, 1993; Opiyo *et al.*, 2007) and there is frequently a gap between knowledge and action (Opiyo *et al.*, 2007) often distorted by attitudes which are frequently not presented or discussed in studies, probably because of the substantial risk of falsely generalising the opinions and attitudes of a particular individual or group (Launiala, 2009). For instance, while it is expected that education would increase knowledge about the cause of malaria, it often does not erase misunderstanding about its cause, such as malaria originating from staying under the sun, being caused by hard work or even witchcraft (Mwenesi *et al.*, 1995; Yadav *et al.*, 2007).

Prior to the review of studies, I identify what the literature says about KAP, which mainly emanates from a body of mixed-methods studies of KAP on malaria. What broadly constitutes KAP on malaria is generally based on the disease and vector. This includes single or multiple statements on the knowledge of causes, symptoms, transmission, prevention, treatment and control measures of the disease; perceptions of the causes, symptoms, transmission, prevention, treatment and control measures, as well as behaviours actually practised to treat and prevent the disease (Agyepong and Manderson, 1994; McCombie, 1996; Njama *et al.*, 2003; Williams and Jones, 2004). Various statements have been posed to individuals and households to respond to these broad categories, and often there is no standardisation. Concerning knowledge, they include the definition of malaria; cause of malaria; differentiation between fever, malaria and severe malaria; government-recommended treatment for malaria; consequences of malaria; dosage of malaria treatment in children and adults; knowledge on vector breeding habitats; times of vector biting; and elimination of vector habitats (Agyepong and Manderson, 1994; McCombie, 1996; Njama *et al.*, 2003; Williams and Jones, 2004). As regards attitude, they include feelings and influences about the knowledge and practice concerning the disease and vector; while practice includes questions, action courses taken on treatment and reducing human–vector contact

(Agyepong and Manderson, 1994; McCombie, 1996; Njama *et al.*, 2003; Williams and Jones, 2004). Scores or coefficients are derived from responses to multiple statements, ranging from one statement to over five (Saeed and Ahmed, 2003a). In addition, the exact questions posed from the studies are mostly unavailable for referral; this has consequences when comparing results across studies.

As this thesis's focus is on the incidence of the disease, this section reviews studies that address KAP and how it influences the occurrences and risks of the disease in different populations. More studies have found the practice and behavioural aspects of KAP more statistically significant than knowledge, and as identified earlier, few studies discuss attitudes.

Several studies have examined the level of knowledge displayed by individuals in relation to the prevalence of the disease. Njama *et al.* (2003) assessed KAP as a predictor of malaria in a caregiver population in urban Kampala in Uganda in a paediatric population. As part of KAP, the level of knowledge variables include questions and statements on causes of the disease and recognition of fever, malaria and severe malaria as well as available treatment options and were considered individually. Questions on attitude pertained to the most important factors that influence treatment choice for paediatric malaria, as well as the best treatment for the disease. Practice questions were focused on the first action to be taken on the appearance of malaria and preventative measures. In assessing this relationship between KAP and malaria, only preventative behaviours, such as use of bednets and anti-malaria drugs, were a significant predictor of childhood malaria. Areas where the density of incidence was highest correlated significantly with places where preventative measures were not observed. Abate *et al.* (2013) studied the relationship between KAP and prevalence of malaria in an urban population by investigating symptoms, causes, treatment, prevention and control behaviours of the disease. The findings revealed that the probability of disease was higher in households that did not practise good preventative behaviours and lower in those that had good knowledge of preventative measures. Similarly, Deressa *et al.* (2007); Alemu *et al.* (2011) and Messina *et al.* (2011) evaluated comparable relationships and preventative behaviours, such as those that destroyed the parasite in human blood (anti-malaria), reduced human–vector contact (ITN usage) and eliminated the vector through use of aerosols and insecticide; these led to significantly lower prevalence of malaria in the population. However, when these

variables, including use of mosquito coil and elimination of vector habitats, were examined by Ernst *et al.* (2009), only the use of mosquito coil was significant in a multivariate relationship leading to decreased prevalence in a population with poor preventative behaviour practices. Saeed and Ahmed (2003a) did not find any significant relationship between knowledge, attitude or practice variables in their population-based study; while 70% of the study population showed good knowledge of the disease and its symptoms, 40% showed poor treatment-seeking behaviour, which had consequences for progression to severe malaria and death.

Across these variables, the practice aspect of KAP, encompassing preventative and treatment-seeking behaviours, have demonstrated more consistent and significant differences on the disease than the attitude and level of knowledge variables. However, what constitutes preventative and treatment-seeking behaviours has varied with the ecological setting, and often their appropriateness has been taken on face value.

This thesis will examine KAP variables in relation to the risk of disease as applied by Njama *et al.* (2003) and Alemu *et al.* (2011) in a similar urban setting.

3.5.6 Travel and Migration

Malaria is an established tropical phenomenon. In these regions, it is reported to be generally lower in the urban areas than in rural communities. A review by Robert *et al.* (2003) confirms this hierarchy of intensity, with malaria being lowest in city centres, followed by peri-urban areas, and highest in rural areas. The flipside of lower malaria prevalence in urban areas is that immunity is also reduced, making urban residents more susceptible to the disease upon exposure. Reduced immunity in the urban populations means that, when urban residents travel to rural areas, they are at risk of malaria infection. Also, when malaria-infected individuals from rural areas migrate to cities, they carry the parasite, which infects the mosquitoes in urban areas and, in turn, urban dwellers that have weakened immunity. Often, rural residents migrate to seek better livelihoods; they bring their culture and way of life with them, thereby ruralising urban environments. Migrants move for other reasons, such as conflict displacement and natural disasters, triggering epidemic malaria such as at the Thai–Myanmar–Cambodian border (Tipmontree *et al.*, 2009). It is in this way that humans move around with elements of the environment, as described by Meade (1977) and Meade and Emch (2010), in the triangle of human ecology disease. Such population movements have also been thought to be the reason behind the resurgence of malaria in highland areas of

Africa (Hay *et al.*, 2002a). The high demand on land from increasing rural–urban migration leaves mainly waterlogged areas, such as swamps and marshlands, as the only available places for new migrants to occupy which as discussed earlier under LULC are vector habitats associated with increase malaria risks.

A number of studies have examined the relationship between travel history, migration and malaria and the findings have been consistent. Studies by Ng'andu *et al.* (1989); Domarle *et al.* (2006); Wang *et al.* (2006c); Baragatti *et al.* (2009) and Peterson *et al.* (2009) in the urban populations in Zambia, Madagascar, Cote d'Ivoire, Burkina Faso and Ethiopia, respectively, revealed a strong positive association between malaria infection and a recent trip to a rural area.

The relevance of this variable to the further understanding of the ecology of malaria in Lagos speaks volumes from the evidence presented, and as such it will be investigated.

3.5.7 Drug Resistance

While drug resistance to malaria is becoming increasingly widespread, it has been mainly blamed for the resurgence of malaria in highland areas of Africa and the Thai–Myanmar–Cambodia borders (Wernsdorfer, 1994; Hay *et al.*, 2002a; Na-Bangchang and Congpuong, 2007). In Ibadan, Nigeria, resistance to first-line malaria treatments has been a significant factor in the delay in clearance of parasitaemia in the blood without recurrence within a paediatric population, and as such leads to increased incidence of the disease (Sowunmi *et al.*, 2010).

While this is an important variable to examine in Lagos state, where the disease is on the increase despite reports of urbanisation being a buffer to an increase in incidence of malaria, this thesis will not examine this variable owing to the limitation of the cross-sectional survey I utilise for my study, which does not offer a clinical setting to achieve this, as applied in Sowunmi *et al.* (2010) earlier discussed study.

This section summarised the role that socio-cultural variables associated with the behavioural vertex of the disease triangle play in influencing malaria risks in multiple locations. Key findings showed that travel history to rural areas; poor preventative behaviours; dimensions of ethnicity and religion were associated with lower incidence; level of knowledge and belief has no significant impact and occupation type, wealth, education are inconclusive in the impact of relationships on malaria infection. Their role will be explored and examined in relation to the occurrence of malaria in Lagos as

potentially important to the understanding of its urban ecology, particularly the role they play from a human perspective and its contribution to locality studies.

3.6 Population Characteristics

Individual differences that can influence our susceptibilities to disease include age, gender, nutritional factors, genetics, underlying health conditions and pregnancy (Meade and Emch, 2010). In malaria risk literature age and pregnancy has been the most studied amongst all and least is genetics.

Age below five years and pregnancy has been as been listed by WHO as risk factors for higher malaria incidence. Age and pregnancy have often been examined in the way it impacts on progress from mild to complicated/severe malaria and its resulting consequences. Many studies have not used 5 years as a cut off age in comparing malaria risk in different populations neither have pregnant women versus non pregnant women being commonly used.

For example Mauny *et al.* (2004) study in Madagascar used less than and greater than 10 years age as the cut off age and findings from the study report that children below the age of 10 years have higher malaria infection. Ayele's (2012) study similarly report a reduction in the risk of malaria with increment in age. In Peterson (2009) study, age is statistically significant with increasing malaria but with children aged 5 to 9 years having higher malaria risks over children less than 5 years and adults. However adults who worked outside at night had higher risks of malaria and children below the age of 5 were protected from malaria because they used ITNs. Though the age intervals used in these studies are different what we note is that more studies report that younger children have higher risks of malaria over older children.

In terms of gender, Ye's (2008) study, reports no significantly associated relationship and this was consistent with Deressa *et al.*'s (2007) and Alemu *et al.*'s (2011) findings in rural and urban Ethiopia respectively. Ayele (2012) reports similar result with no gender in particularly greater risk of malaria apart from pregnant women who have been reported by WHO as an at risk group. Human genetics is one of the risk factors under population vertices of the HED (Meade and Emch, 2010) and rarely occurs in malaria risk studies possibly because of the experimental setting it requires to examine it. Nahum *et al.* (2010) examines having the sickle cell trait in relation to malaria and the finding show that it served as a protective shield and is a statistically significant with decreased malaria infection.

Key findings show the importance of age, pregnancy and genetics in relation to malaria risk. As this study utilises a household approach, it will look at age below 5 years and pregnancy as factors that make a household vulnerable.

As mentioned earlier, the framework of disease ecology has featured predominantly as an applied approach, and will be useful in examining these identified variables in the study location of Lagos.

3.7 Theoretical Framework

My research employs the theory of human ecology of disease (Meade and Emch, 2010) to examine the important variables identified from the review to be relevant in the understanding of the urban ecology of malaria. The framework offers the theoretical benefit of assessing the multiple factors associated with the environment and behaviour in relation to the disease outcome. This environment is that which humans and anopheles vectors inhabit, and due to vector and human behaviour, interact closely to result in disease transmission.

It has been translated to make meaning for urban malaria in this research (Figure 8). The framework recognises that vector-borne diseases result from a synergy of linkages and interactions of variables between humans, the vector, the parasite and the environment. Here it consists of the physical and built environment and behavioural variables that interact with humans, depicted here as the population infected by malaria. The environment, the disease, vectors and humans do not exist separately; they interact synergistically, and malaria is encouraged through these numerous ways. This framework, then, allows us to model real-life situations in order to identify the most important pathways for malaria transmission and develop intervention strategies that will address this. Through this, we can understand the ecology of the disease, by unpacking these qualitative and quantitative relationships with malaria. However, modelling these complex relationships and interactions is fraught with difficulties and we are often left to break them down to develop a relationship, as noted earlier by Meade (1977). Despite its weakness, the study of malaria and human behaviour in an ecological setting is a fundamental task for medical geographers, thus employing the approach will contribute to basic and applied research in the discipline. It provides a strategy to answer arising questions on urban malaria in the sub-discipline.

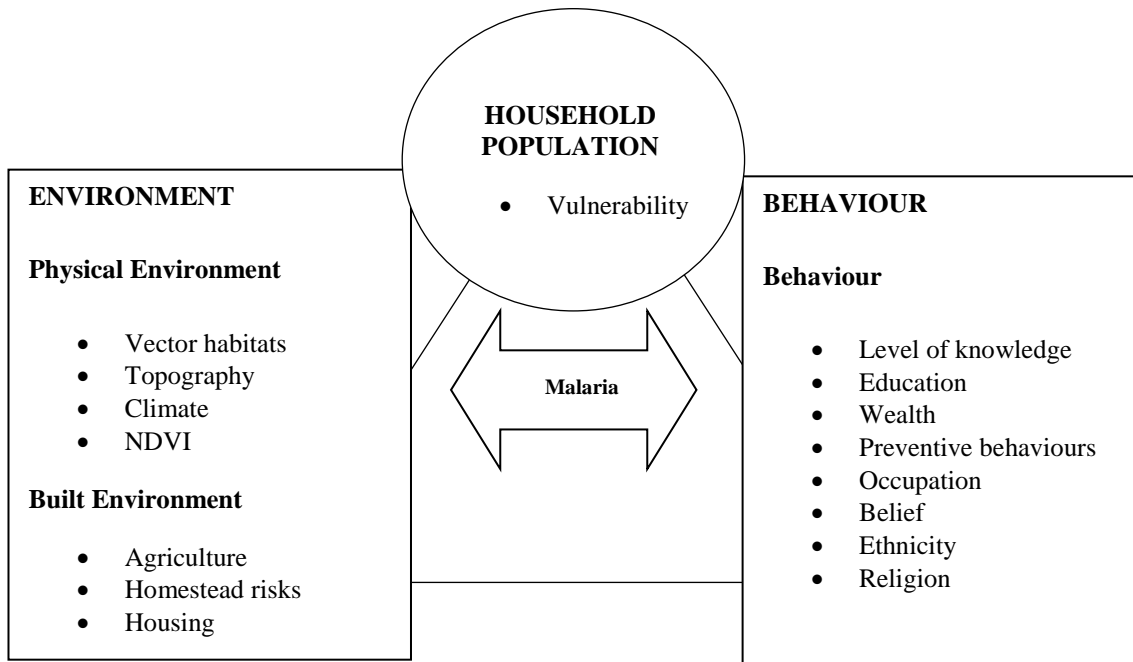


Figure 8: Adapted human ecology of malaria framework

3.8 Data Quality Issues in Malaria Infection Data

Many data quality assessment studies have been conducted for health data. Although the literature covers a wide variety of these, this section will focus on identification and definition of data quality dimensions that appear repeatedly in the literature and the way they have been applied to assess malaria infection data and their reporting frameworks.

One of the main sources of malaria data is the routinely collected hospital-based clinical data or population-based active disease surveillance. Data collected via patient visits to health care facilities mostly represent severe cases of malaria owing to the treatment-seeking behaviour of the population; therefore, clinical malaria data underrepresents actual levels of disease in communities (Abeysekera *et al.*, 1997). Apart from underrepresentation, data on infectious disease of which malaria is one, is generally characterised by other quality issues (Thacker *et al.*, 1983), as also acknowledged by WHO (2008). This has implications for surveillance, monitoring and evaluation of progress made through interventions. Despite this, studies do not often account for quality in datasets in their findings or undertake a quality assessment of malaria data as a standalone research. Where this has been done, a limited number of data quality dimensions have been applied to assess only the data, not the quality of the reporting framework that produces this data. In addition, what constitutes data quality has varied.

From the literature, some of the conceptual definitions presented are “fitness for use” or “fitness for purpose”, and “more than just data accuracy and completeness to include other dimensions that describe data at an instance” (Wang and Strong, 1996; Batini and Scannapieco, 2006). To describe data quality, dimensions such as accuracy, precision, interpretability, reliability, completeness, timeliness, currency, interoperability, metadata, accessibility, objectivity and relevancy have appeared in the literature. The definitions of each dimension derived from literature are presented in Table 1. They have been applied to examine the quality of malaria infection data as well as to assess the quality of the institutional data-generation, management and reporting framework. A number of studies have applied some of the dimensions in Table 1 to examine the quality of routinely collected malaria infection data or population-based surveillance data. Often, quality issues have been detected.

Abeysekera *et al.* (1997) examined how boundary issues and proliferation of the health systems with private health care providers affected the accuracy of malaria data. Findings showed that patients crossed health boundaries to health care providers in another jurisdiction and private health care providers did not properly record their malaria patients and where they did, it did not feed into the Sri Lanka health system because it did not take into consideration private HCFs or boundary issues.

Van Hest *et al.* (2002) and Alaya-Bouafif *et al.* (2011) examined completeness and underreporting issues for imported malaria cases from three sources (laboratory registers, notification office and hospital admissions) and their consequences for accuracy and reliability using capture-recapture methods in the Netherlands and Tunisia respectively. Capture-recapture methods calculate the number of cases in each data source and the number common to all data sources put together. Findings showed completeness and underreporting issues for all data sources, but while the laboratory data source had the highest completeness in Van Hest *et al.*’s (2002) study, the notification registry did so in Alaya-Bouafif *et al.* (2011).

Table 1: Data quality dimensions and their definitions for applied usage

<i>Dimensions</i>	<i>Definition</i>	<i>Definition references</i>
Time-related dimensions	Describes when data is up to date, age of data, how promptly data is updated, and when data is acquired or available on time, as well as length of time data remains valid. Also includes currency, timeliness, up to datedness, volatility.	GFATM (2009); Wand and Wang (1996); Wang and Strong (1996), Batini and Scannapieco (2006)
Reliability and consistency	The extent to which data is always presented in the same format and is compatible with previous data. Inconsistency occurs when there is more than one state of the information system matching a state of the real system.	Wand and Wang (1996); Wang and Strong (1996)
Accessibility dimension	The extent to which data can be restricted and hence kept secure. This measures the ability of the user to access the data from the perspectives of own language, culture, physical status/functions and technologies available. The extent to which data is available or easily or quickly retrievable. The ease with which the user can obtain the data analysed by cost, time frame, format, confidentiality, respect of recognised standards, copyright, etc.	Batini and Scannapieco (2006); Wang and Strong (1996); Bedard and Valliere in Devillers and Jeansoulin (2006)
Flexibility	The capacity for a view to change in order to accommodate new demands. The extent to which data are expandable, adaptable and easily applied to other needs.	Wang and Strong (1996); Levintin and Anany in Devillers and Jeansoulin (2006)
Relevancy	The degree to which a view's components are pertinent to satisfy intended applications. The extent to which data is applicable and helpful for the task at hand. Not a common DQ dimension.	Wang and Strong (1996) ; Levintin and Anany in Devillers and Jeansoulin (2006)
Free of error dimensions and exact representation	Exact representation of the real-life value, to include accuracy, validity, correctness, negligible error, precision, and data measuring what it is intended to measure, minimal error to the point of being negligible. Can be presented quantitatively or qualitatively.	GFATM (2009); Wang and Strong (1996); Wand and Wang (1996); Batini and Scannapieco (2006); Pipino <i>et al.</i> (2002); Devillers and Jeansoulin (2006) Burrough and McDonnell (1998); ISO 3534-1
Completeness	Complete or partial coverage of features, their attributes and relationships. Having all relevant information recorded. Includes underreporting.	Wang and Strong (1996); Batini and Scannapieco (2006); Tayi and Ballou (1998); Wand and Wang (1996); Redman 1996 in (Batini and Scannapieco, 2006); Jarke <i>et al.</i> (1999); GFATM (2009); Pipino <i>et al.</i> (2002)
Reputation attributes	Also known as reliability, believability, integrity and objectivity. It is described as data that can be counted on to convey the right information without deliberate manipulation. The extent to which data is unbiased, unprejudiced and impartial, true and credible.	Wand and Wang (1996); GFATM (2009); Devillers and Jeansoulin (2006); Pipino <i>et al.</i> (2002); Wang and Strong (1996)

Erhart *et al.* (2007) assessed the accuracy of malaria data gathered through active case detection and routine hospital data in Vietnam. The evaluation included the examination of the data-generation and reporting system using a mixed-methods approach. The findings revealed duplication of data reporting, lack of consistency and higher accuracy of active case detection data when compared to hospital data. Similarly, Chilundo *et al.* (2004), in a descriptive mixed-methods study, evaluated the quality of routinely

collected malaria data and the reporting framework of the Mozambique health service system using quality indicators such as completeness, accuracy, consistency and timeliness. This study equally demonstrated quality issues with malaria data using the mentioned dimensions.

In summary, findings from the earlier studies show that quality issues are inherent with routinely collected malaria data. However, quality has mainly centred on completeness and accuracy dimensions and less on other dimensions presented in Table 1. Some of other important dimensions such as data format, accessibility and relevancy issues that have significances for the direct or immediate use of data are lacking. These are also limited studies on timeliness and the framework for reporting. None of the data quality studies conducted after 2009 have applied the Global Fund for Aids Tuberculosis and Malaria Data Quality Audit (GFATM DQA) (GFATM, (2009) tool apart from Gimbel *et al.* (2011) who uses a similar bottom up approach in assessing routine primary care data (not malaria) in Mozambique. The tool was developed in 2009 purposely by The GFATM and the MEASURE Evaluation project to exclusively assess and improve the overall DQ on Malaria, HIV and Tuberculosis indicator data.

The tool kit offers a bottom up approach in data quality assessment starting from the time of diagnosis of malaria to the national or the highest reporting level in a country's system. It is based on the system assessment protocol and a data verification protocol conceptual framework. This conceptual framework is based on the notion that both the system and data the system produces must be assessed in order to truly say malaria data is of a certain quality. Meaning a poor system cannot produce good quality data. It relies on seven DQ dimensions: accuracy, reliability, precision, completeness, timeliness, integrity and confidentiality and the emanating results are both qualitative and quantitative outputs.

Two versions of the GFATM DQA tool were developed by the team. One is for large scale detailed external auditing known as the DQA while the other is a smaller scaled simplified version called "The Routine Data Quality Assessment Tool" (RDQA) and is to be used routinely by a project/program wishing to assess its data quality. This research will use a scaled down and adapted version of the DQ tool to assess routine malaria infection data collected and used in this research.

3.9 Conclusion

This chapter on the literature review concludes by building on knowledge gained from the previous chapter towards identifying and re-affirming gaps in the literature and areas where this research will contribute its share of knowledge.

In Chapter Two I reviewed existing research on Nigeria and particularly Lagos state. Most evidence relates to behavioural aspects of malaria which is outside the scope of this study focusing on the incidence of the disease. The lack of relevant studies on the geography of malaria, and the need to increase knowledge on the ecology of urban malaria in Nigeria and West Africa as a way of addressing the disease has been raised by Brieger *et al.*, (2001) and WHO current strategy to target highest burden countries of which Nigeria tops seems to be in agreement with this. Through this approach WHO hopes to meet its target of a 75% reduction in malaria by 2015 (WHO, 2012). I subsequently identify the human ecology of disease framework as an appropriate lens through which human malaria environment interactions can be viewed and understood. Therefore, I employed this framework for my thesis to review studies as well as to achieve the research objectives stated at the beginning of my research.

To progress with the study on the urban ecology of malaria in Lagos state, this chapter has drawn on evidence from studies conducted in other localities in Africa by reviewing over 82 articles and 35 supporting studies. The studies are presented and discussed by relating them to risk variables associated with the behaviour and habitat elements of the triangle of human ecology of disease. In summary, a broad range of risk variables that have been identified to have known and uncertain statistical significance will be collected, explored and examined in relation to the occurrence of malaria in Lagos state. At the end of the research, I will assess their importance for this particular locality in order to narrow down to a set of variables or to recommend for further research.

Climate is an important risk factor that controls the presence of vector habitats and the abundance of the anopheles mosquitoes with likely consequences for increased malaria risks. Across the literature reviewed, the overarching influence of temperature over relative humidity and rainfall at broad spatial scales and peri urban areas using multiple time lags in tropical Sub-Saharan Africa is known (Tanser *et al.*, 2003; Ezzati *et al.*, 2004; Pascual *et al.*, 2008; Ye *et al.*, 2008). There has been little or no focus on purely urban areas like Lagos state characterised by anthropogenic urban heat (Changnon, 1992; Ichinose *et al.*, 1999; BNRCC, 2012) under multiple temporal scenarios apart

from Tay *et al.* (2012) study in a smaller city Accra and concentrating on a short time period and Oluleye and Akinbobola's (2010) in Lagos looking at only temperature and rainfall without relative humidity or the effects of time-lags on the disease transmission¹⁴. This study will build on Oluleye and Akinbobola's (2010) study in Lagos and examine the temporal patterns in disease risks and additional climatic variables (rainfall, relative humidity and temperature), investigating their influence over a longer time period at different biologically plausible time-lags.

In line with Reiter's (2001) and Lafferty's (2009) suggestions to consider and quantify non-climate factors, this review of literature revealed other variables important in understanding the ecology of the disease in Lagos state. While the risk variables are not always statistically significant or positively associated with malaria, many of them yet remain relevant for understanding the ecology of this study location.

From the review of literature, topography in the form of elevation, slope and other derivatives of elevation, such as the topographic wetness index and topographic position index were consistently significant with malaria infection but more relevant in highland areas. I will however consider the role of slope and elevation for malaria infection in Lagos state, as most relevant for a heterogeneous lowland area.

The way agricultural practices influence malaria transmission risks in Lagos state is unknown. This thesis will therefore study the relationship between proximity of households to agricultural sites in relation to the risk of malaria, as identified by Afrane *et al.* (2004), Klinkenberg *et al.* (2005) and Yadouléton *et al.* (2010) to be a significant risk variable for urban malaria. Agricultural practices include farmlands and commercial animal husbandry sites. It will also look at characteristics of homesteads that have been reported to harbour the anopheles such as the presence of water, vegetation and livestock domestic containers, wells, open drains and puddles of water and, in turn, increase malaria infection (Adeleke *et al.*, 2008; Yamamoto *et al.*, 2010; Olayemi *et al.*, 2011).

Just as literature by Klinkenberg *et al.* (2005), Ye *et al.* (2008) Peterson *et al.* (2009) and Yamamoto *et al.* (2010) show that some form of relationship exists between a range of housing characteristics and malaria, where the characteristic represents the presence of an avenue for mosquito entry. My study will also investigate these by assessing the

¹⁴ Findings have been discussed under climate section of this chapter

contributory extent of housing characteristics (window and door nets, household size and room density, as well as the condition of walls and roofs) to the risk of disease where the best measure to represent housing will be locally driven.

With respect to variables associated with the behavioural vertex, what is important at global scales e.g economic status may at local scales become unpredictable. Rural–urban migration has been the most consistently significant variable (Baragatti *et al.*, 2009). This is followed by preventative and treatment practice, an aspect of KAP, which studies recognised as having a persistent influence on disease risk patterns (Njama *et al.*, 2003). Exposure from outdoor occupations is another significant variable that influences malaria prevalence (Yapabandara and Curtis, 2004).

There are also other variables such as ethnicity, religion and culture, and education that have presented inconsistent significances in their relationship with malaria prevalence owing to the use of unstandardised measures of the variables, cross-country comparisons, or lack of statistical power (Njama *et al.*, 2003; Ye *et al.*, 2008). These variables will still be examined in an exploratory mode to determine if there are initial patterns that may require further investigation.

Variables such as drug resistance, access to HCFs and genetics that have been reported as important for mild and severe malaria and its consequences, as well as surges in malaria rates (Wernsdorfer, 1994; Baume *et al.*, 2000; Saeed and Ahmed, 2003b), are not examined in this research, owing to limitations in the cross-sectional study design adopted such that data on drug resistance and severe malaria cannot be gathered reliably as is possible in experimental designs (Hennekens, 1987).

As earlier noted, statistically significant, insignificant and inconclusive variables examined in other localities, and others not examined will be considered in this research to develop knowledge on them for this locality. As it will be used to develop and understand a predictive model of the human ecology disease, its application will foster better understanding of the conceptual framework which is a dominant discourse of the sub-discipline of medical geography. With the focus of my research being Lagos state, I will narrow down on variables important for urban malaria in this locality and create new knowledge that did not exist. Through it, my research will contribute to theoretical and methodological knowledge of “place” and ecology of urban malaria as one of the original thesis of its kind that examines such breath of variables in this locality.

Chapter Four: Research Methods

4.1 Introduction

This chapter documents effort in research design, data-gathering (household survey, secondary data sourcing and interviews), processing and analysis methods, and ethical considerations used in the study. These strategies are informed theoretically by the literature and the study context.

4.2 Study Area: Lagos, Nigeria

The intention to undertake my research in Lagos state, Nigeria and with a specific in-depth study of Ikeja and Kosofe LGAs is based principally on:

1. The rise in the total number of malaria cases by 77.3 % (351,222 in 2000 and 622, 562 in 2011) and malaria in pregnant women by 124.3% (from 13,826 in 2006 to 31,007 in 2011) despite several intervention strategies employed (LSMoH, 2010; 2011).
2. Its status as one of the top five contributors to the malaria burden in Nigeria.
3. Its status as the largest urban population in Africa and current growth rate of 3.75%, which will make it the 14th largest urban agglomeration in 2015 (UNDESA, 2012).
4. Its heterogeneous topographic, demographic, cultural and ecological characteristics of Ikeja-Kosofe LGA.

A preliminary assessment of malaria infection reports from health care facilities situated in each local government area in Lagos state reveal Ikeja and Kosofe to be major contributors to the disease burden in the state. These LGAs record over 180 cases per 1000 in the state. The health care facilities in Kosofe LGA report an annual number of cases of about 20,000, while Ikeja reports about 35,000, making Ikeja the 2nd highest LGA reporting over the period 2000–2009 (see Chapter Six). They have also been a

focus for many Eko Free Malaria Project intervention strategies yet remain huge contributors in the state.

Lagos state, Nigeria has a population of over nine million (Table 2). It is situated along the West African coast and is the commercial capital of Nigeria. It consists of the Lagos Mainland and pockets of islands known as Lagos Island.

Table 2: Key population characteristics of Lagos state

Population Characteristics	
Geographic location	6° 27' 11" N, 3° 23' 45" E
Population size	9,113,605 (male: 4,719,125, female: 4,394,480)
Area size	3,496.5 km ²
Population density	2607 persons km ²
Population growth rate	3.75%
Gender ratio	107/100 (male/female)
Ethnic groups	Indigenous Aworis and Ilajes and other Yoruba tribes
Languages	Main local language is Yoruba; others spoken are the main Nigerian languages, which are Igbo, Hausa and other minority tribe languages. Working and official language is English
Religion	Christian, Muslim, Traditionalist, Atheist
Literacy	25% achieved beyond secondary school, 41.3% have secondary school education, 33% did not achieve up to secondary school, out of which 15% cannot read or write a complete sentence
Administrative divisions	25 LGAs and 52 local government development authority (LCDAs)
Housing and household characteristics	2.27 million households (96.7% regular; others are institutions, homeless and transient households)
Main occupations	Most people are traders; others are skilled manual labourers, farmers, fishermen and transport workers, with professional workers accounting for the lowest proportion

Source: Federal Republic of Nigeria (2007) and Lagos Bureau of Statistics (LBS) (2012)

Lagos state has one of the highest annual urbanisation rates of 3.75% in Africa and has a high birth rate signified by the shape and large size of the base of population pyramid in Figure 10. As shown in the figure, population size declines shortly after 0 years until about 10 years, and according to Ayeni (1980) and Adegbola and Chojnacka (1984), loss of life at this age occurs mainly from malaria, diarrhoea and other respiratory infections. The impact of malaria diminishes from about 5 years leaving loss to other illnesses earlier mentioned which continue throughout childhood.

After 10 years the population increases gradually until a boom occurs about 20 to 25 years, owing to prosperity and marriage-led migration (Watts, 1983; Kearns and Joseph, 1993). Between 25 and 30 years, a population decline occurs until about 75 years. According to Adegbola and Chojnacka (1984), Kearns and Joseph (1993) and Enweluzo *et al.* (2008), while this may generally be attributed to migration, loss of life for men

engaging in risky professions and behaviours (motorcycle transport and highway hawking) leads to vehicle accidents and accounts for about 26% of deaths. Deaths in childbirth account for women's losses. Other reasons for the population pyramid shape at this age are migration to smaller urban or rural areas due to change of marital status (divorce, widowhood) and retirement, as well as death attributed to hypertension and heart disease (Ayeni, 1980; Watts, 1983).

Ikeja and Kosofe LGAs, where the in-depth studies are carried out, have a total size of 130km² and populations of 313,196 and 665,393 respectively (FRoN Official Gazette, 2007). Ikeja and Kosofe have 44 localities each as shown in Figure 9 insert, and 855 and 1,531 enumeration areas (EAs) respectively. Abule Oloti locality has the smallest size area of 0.2km², while Agboyi locality has the largest: 14.25km². These both fall within the mainland part of Lagos state which has been selected for in-depth study on the basis of elevated disease rates (Chapter Six) and other ecological characteristics itemised earlier.

4.2.1 Socio-economic Characteristics

In Lagos, about 60% of residents are medium income earners, highly mixed amongst other income groups across the state: a characteristic that depicts urban areas in developing countries (Robert *et al.*, 2003). They engage in trade, semi-skilled or highly skilled professions and also partake in full-or part-time urban agriculture (Appendix I). The indigenous ethnic communities of the Aworis and Ilajes, irrespective of their socio-economic backgrounds, cluster around riverine areas, living in houses typical to their culture, as shown in Appendix II. While they are mainly fishermen, they also participate in sand dredging and water transport.

Residents mainly live in the mainland or peripheries of Lagos state and commute long distances on a daily, weekly or monthly basis for economic purposes. Often people also take temporary accommodation in Lagos state during the week and return to their distant home at the weekend.

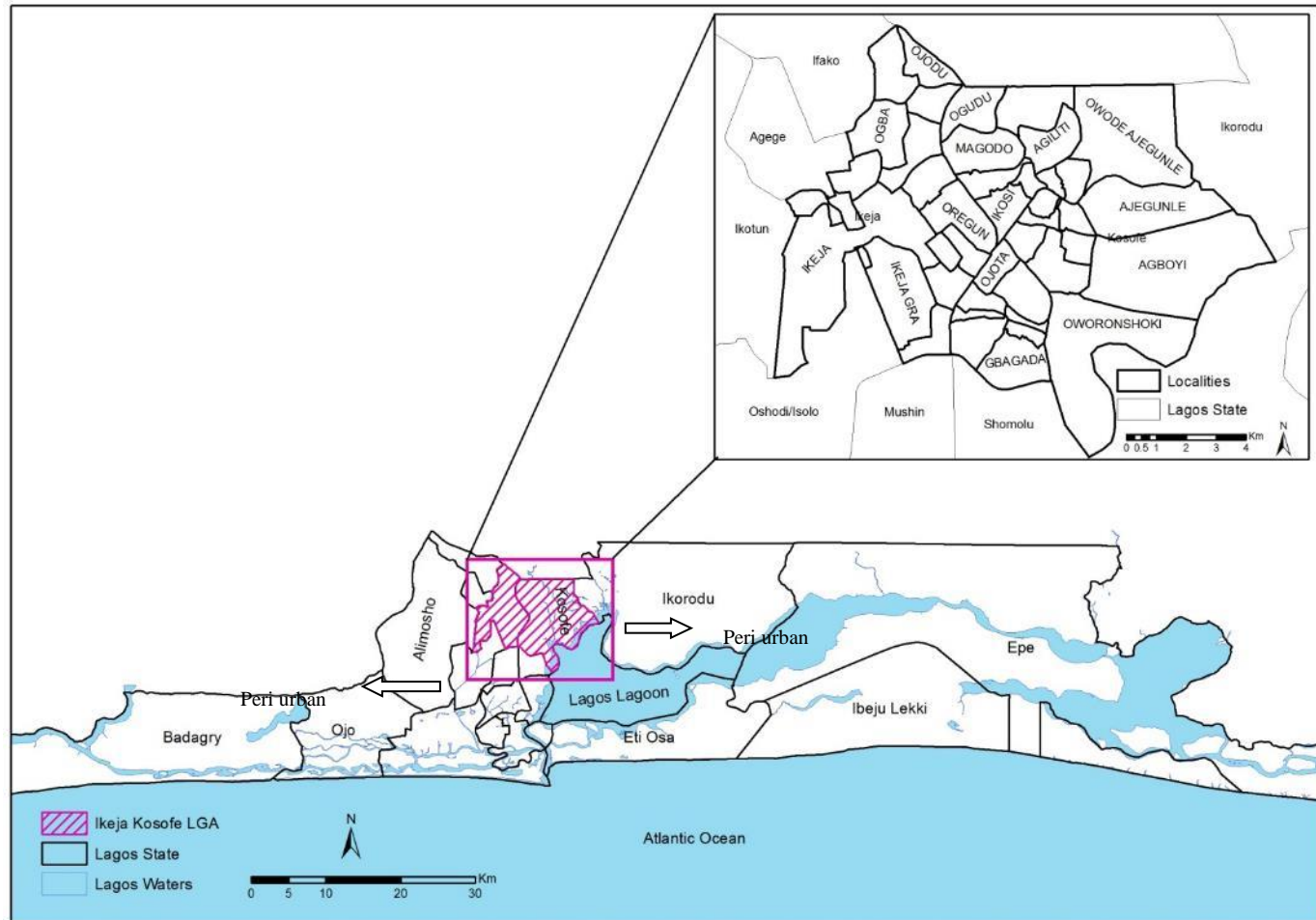


Figure 9: Map showing localities of Ikeja and Kosofe LGAs in Lagos state, Nigeria

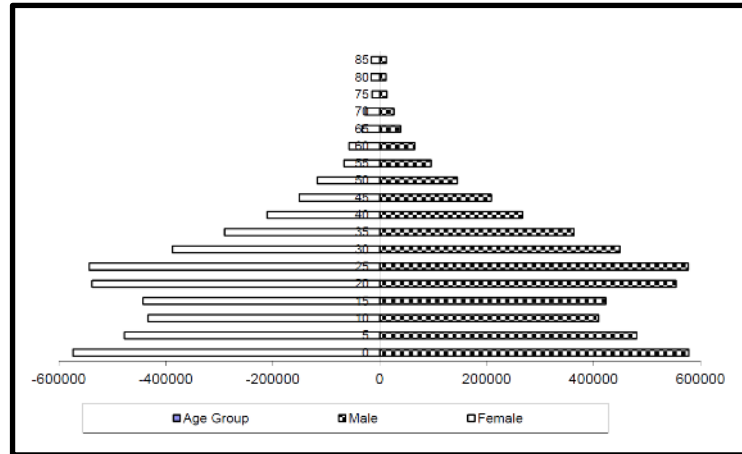


Figure 10: Lagos state population pyramid

Source: Lagos Bureau of Statistics (LBS) (2012)

4.2.2 Climate and Topographic Characteristics

Lagos has two wet seasons (long: April to July; short: September to October) and two dry seasons (long: November to March; short: distinct August break). The wet season has two rainfall peaks per year- in July and September. The highest amount of rainfall occurs between April and July, with July recording as much as 600mm and April as little as 37.4mm. The total wet season rainfall can be as high as 1817mm, and 138mm in the dry season. A minimum of 86% of all rainfall occurs in the wet season. Relative humidity is high all year round with an average of about 86%. The mean monthly temperature is about 27.5°C and the maximum recorded in recent years exceeds 38°C (BNRCC, 2012). As a coastal state, the majority of the area is below sea level and other parts are flat. In Ikeja and Kosofe LGA, elevation is between -11m and 54m.

4.3 Research Design

My objective is to assess the relationship between variables in a varied sample of households in a particular snapshot and the cross-sectional design meets this need (Alemu *et al.*, 2011). It is relatively quick and easy to implement but susceptible to bias and misclassification from a low response rate and recall bias respectively (Hennekens, 1987).

The cross-sectional design (Figure 11) implemented in two phases (pilot study and main study) employs a mixed-methods strategy (Tang *et al.*, 1995) to gather data on a sample of households in Lagos state. A mixed-methods approach to inquiry combines both quantitative and qualitative forms of data collection, analysis and presentation

(Tashakkori and Teddlie, 2003). The quantitative aspect forms a major part of the methods and the qualitative aspect forms a minor one.

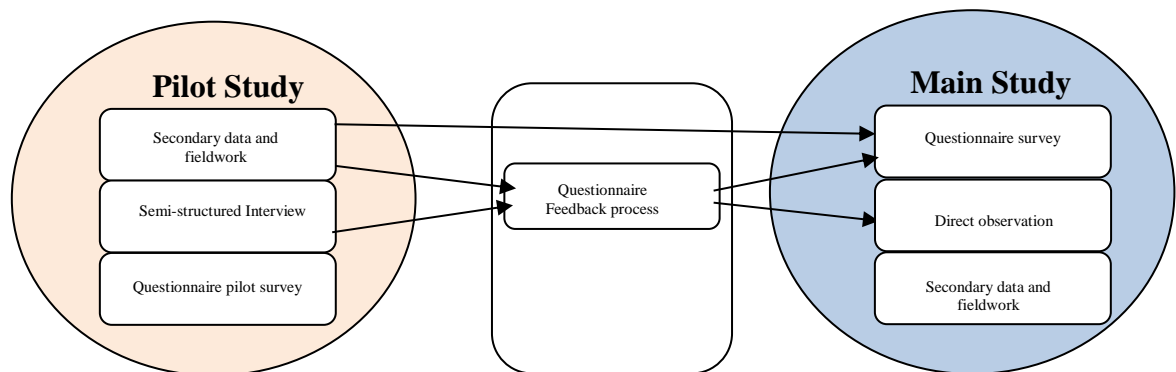


Figure 11: Study design

The qualitative method consisted of a semi-structured interview to gather behavioural and culturally sensitive information at the pilot stages, which was later processed, converted to quantitative data and fed into the improvement of the questionnaire. The quantitative aspect consisted of a questionnaire survey tested in the pilot stages and later improved using semi-structured interviews and administered to a cross-section of households in the main study phase. Other quantitative data collection methods utilised were GIS and remote sensing information on household environment, as well as direct observation data (Matthys *et al.*, 2006b; Machault *et al.*, 2010). These datasets generated represent numeric descriptions of variables affecting households and were used to examine trends and relationships amongst the variables. The semi-structured interview was also utilised in the main study as a place-sensitive approach to capture everyday experiences and used as a backdrop to enhance the explanation of quantitative findings (Kearns, 1993; Cutchin, 2007; Creswell, 2009). In summary, they were used for data collection, development of research instruments and explanation of relationships.

Employing a mixed-methods approach had a number of advantages and disadvantages. Firstly, it drew on the strengths and minimised the weaknesses of both approaches, and in so doing, improved the overall quality of the study; but the price of this was that it was resource-intensive (Johnson and Onwuegbuzie, 2004; Creswell, 2009). The semi-structured interview helped to fill in missing items of information to explain

quantitative relationships that otherwise could not be known for specific ungeneralisable locations (Cope, 2010). I lost information during qualitative to quantitative data conversion, as well as quantitatively simplifying real-world complexity (Field, 2010). The questionnaire limited participants' ability to express their voices (Tashakkori and Teddlie, 2003). However, these effects were mitigated through the use of the mixed-methods approach employed in both pilot and main study phases.

4.4 Household scale based approach

Household based approaches is an approach that works “from within” rather than singling out an individual and work “from without”. It is an approach commonly used in family well-being, gender relations and income issues by international agencies such as United Nations and World Bank in developing household based metrics to represent economic status. The approach has been found to be a more sustaining approach with huge rewards (Henriksen *et al.* 2010).

The standard approach focuses on individual experiences of malaria and its risks. Even though this approach tells the story of individual risks, it neglects the story of the household from which the individual comes from, a burdened household that often may experience similar risks and experiences to that of the individual. Thus, while the household approach diverts from being standard, I use it because it challenges the intricacies and risks from within and represents it collectively at the household level. In so doing, I aim to represent the burden and risks at household level irrespective of the individual members that have recorded the disease.

Thus, I have selected household as the unit of analysis in order to account for the burden which households encounter when any member of the household irrespective of age experiences the disease. When malaria or its consequences such as death occurs in any household member, the household as a whole feels the loss and is thus impacted emotionally, socially, economically or otherwise, making it a burden for not just the individual but the household. This approach is thought to offer the advantage of relating malaria as a burden unto that household and less as an individual experience owing to the way every member of a household is impacted (socially, financially, emotionally, psychologically) from the disease irrespective of who gets infected. It looks at the risks arising from that household and how this could have contributed to the occurrence of malaria within that household.

A number of studies in malaria risks have employed this approach successfully. Some examples are Afrane *et al.* (2004); Kibret *et al.* (2010) and Ngom and Siegmund (2010). These studies have not only represented single or multiple individual accounts of malaria on a household level, but also developed socio-cultural and environmental risk metrics used in individual and population based studies at a household scale. The household approach thus represents risks and occurrence of malaria as a risk to a burden on the household in a sustaining and encompassing way (Henriksen *et al.* 2010) for this research. This is not without its weaknesses such as the difficulties of comparing results across societies with differing household structures.

4.5 Pilot Study

The pilot study took place between March and June 2008 (the latter part of the dry and the early part of the rainy season). It formed an important aspect of my study design because it served as a platform to identify study locations, develop and test my research instruments/protocols, evaluate resources needed (human, financial and training needs) and potential future problems (van Teijlingen and Hundley, 2001). As preliminary steps to the pilot study, I sought permission through the University of Lagos, Akoka, Nigeria (Appendix III) to undertake the study, and obtained permission under the Eko Free Malaria Project, with the ethical approval attached as Appendix IV.¹⁵

The pilot study consists of a secondary data collection, pilot test of questionnaires and administration of semi-structured interviews, development of sampling framework and analysis (Abate *et al.*, 2013). The secondary data collected are clinical malaria infection, meteorological and entomological information. I explored the spatio-temporal patterns of clinical malaria in Lagos state to identify Ikeja and Kosofe LGAs as a location with elevated disease rates (Chapter Six) and other peculiar ecological characteristics such that they became the focus for subsequent stages of the research. As secondary data are often purpose built, I made do with their limitations (Paul White, 2010) and where possible improved their quality with fieldwork, as performed for the entomological datasets.

The pilot study was hybrid, in the sense that the semi-structured interview data was used to develop new questions and improve the quality of the questionnaire (Tang *et al.*,

¹⁵ Though this project has ethical approval which I followed during data collection, I should still have obtained a prior ethical approval from Newcastle University, UK.

1995; Imbahale *et al.*, 2010) and the same data on people's experiences was also carried forward into the main study (see Figure 11).

I worked with two field assistants with good local knowledge¹⁶ who were trained on the theoretical and methodological aspects of the questionnaire, sample recruitment, its administration and GPS mapping (Imbahale *et al.*, 2010). We worked as a team to pilot the questionnaires and develop the sampling framework, while I conducted the semi-structured interviews single-handedly.

4.5.1 Study Population, Sampling Frame and Strategy

The study population is a cross-section of all spouses/heads of households above the age of 18 years living in Ikeja and Kosofe LGAs. These do not include any who work in this location but live elsewhere, or visitors within the area at the time of interview.

In the absence of an appropriate sample frame such as a voters' register (Parfitt, 1997), for both the semi-structured interview and the pilot questionnaire, we recruited participants using a combination of a map of the Ikeja and Kosofe LGAs (Figure 9), a list of localities within the LGAs (Figure 9 insert) and local knowledge. We used them to navigate our way around the locations, identify and select households randomly by walking along the street; we made an initial visual assessment of buildings and a preliminary conversation with head/spouses of household to assess their socio-cultural characteristics and then requested an interview (Marshall, 1996; Malterud, 2001). This was relatively easy to carry out, as many households in Lagos live an outdoor life, as shown in Appendix V, where a participant is being recruited. To create a natural environment as much as possible, all interviews (questionnaire and semi-structured interviews) were conducted at the participants' places of residence.

During the fieldwork, we identified/clarified street names, landmarks, features and boundaries for the development of a map sampling frame for use in the main study.

4.5.2 Semi-structured Interview

The semi-structured interview was a verbal, conversational and informal interchange of approximately 30 minutes between myself (the PhD researcher) and 18 theoretically appropriate information-rich participants residing in Ikeja and Kosofe and Ikorodu LGAs. This was to gather information on sensitive and difficult aspects of everyday

¹⁶ They were postgraduate students from the University of Lagos who would also participate in the main study.

lives concerning malaria in a less intrusive and resource-intensive way than a focus group discussion (Barriball and While, 1994; Longhurst, 2010).

The participants were selected through a purposive sampling strategy as described in the previous section. To achieve maximum variation in the sample, these participants had diverse social, economic and ecological characteristics and resided in different geographic locations. Thus from the data generated, these participants could be classified into these sub-categories (Tang *et al.*, 1995; Bryman, 2012). I verbally briefed participants, requested an opt-in and informed consent using the information sheet in Appendix VI and proceeded with the interview where applicable using the protocol in Appendix VI (Valentine, 2001). The socio-demographics of these participants are presented as Appendix VII.

I utilised a notebook, because despite the participant's full understanding of the research objectives, they were still uncomfortable using a tape recorder (Barriball and While, 1994; Corbetta, 2003; Bryman, 2012). The notebook approach was advantageous in this context because it did not encounter any malfunctions, it was more practicable under unstable power-supply conditions required to power batteries, replay and make daily transcriptions, but I faced difficulties with participants who spoke quickly, which may mean that I missed out important quotes or verbal gestures like sighs (Opdenakker, 2006; Tessier, 2012). However, I followed up any unclear interviews.

4.5.3 Questionnaire Survey

I developed the questionnaire survey, as attached in Appendix VIII, with support from the Nigerian Demographic and Health Survey (DHS) of 2003 and literature such as Brieger *et al.* (2001); Njama *et al.* (2003); Uzochukwu and Onwujekwe (2004); Isaac and Adejoke (2007) and Okafor and Odeyemi (2009). The questionnaire was characterised by multiple choice and some open-ended questions (Njama *et al.*, 2003; Bryman, 2012), and due to its structured and characteristic close-ended questioning mode, it could have been restrictive for participants when responding to questions (Creswell and Plano Clark, 2007; Bryman, 2012). Its mode of data collection was a paper-and-pencil interviewer-administered process similarly known as PAPI¹⁷ (Bowling, 2005). Though this mode is notorious for its cost implications over telephone or internet modes, it is preferred where lack of literacy limits the study population or where additional investigations in the households are part of the survey, as in similar

¹⁷ Face-to-face verbal interview using traditional paper-and-pencil-interview (PAPI) questionnaires.

urban malaria studies (Fowler, 2009; Yamamoto *et al.*, 2010). One similar and important source of data is the Nigerian DHS of 2003 (National Population Commission, 2004) has a poor spatial coverage and currency for my study area.¹⁸

As shown in Appendix VIII, apart from introductory sections that included overall information and informed consent, there were five question sections. The first section on malaria consisted of questions on self-reported malaria in the last month and year in household population, the time and frequency of occurrence and knowledge, and mosquito net usage. The second section asked questions on health care facility (HCF) usage and physical access issues. The third section concerned questions on housing characteristics and amenities where participants are asked about the condition of different aspects of their houses. Section four was on economic characteristics and contains questions on income and assets, while the last section focused on socio-demographic characteristics. Each page had a comment section to provide feedback on: a) whether or not participants asked for clarification; b) whether or not participants provided an inadequate answer that required further probing by the interviewer; c) whether or not the question posed a difficulty for the interviewer to ask (Fowler, 2009) and any other comments/questions that might arise.

This questionnaire was piloted and tested for its contents and validity with the aid of field assistants to 51 participants (spouses/heads of household) from households drawn from the same population in Ikeja and Kosofe LGAs where the main study is to be carried out. The participant recruitment process was as described in the previous section. The spouses/heads of households were targeted as the main respondents because they were considered to be the most knowledgeable and influential in the household (Fowler, 2009).

4.5.3.1 Sample Size

While information redundancy formed the criteria for reaching an appropriate sample size in the semi-structured interviewing, for the pilot questionnaire survey three criteria were paramount in determining the appropriate sample size. Firstly, a sample size equivalent to 10% of the final sample size of 505¹⁹ (Lackey *et al.*, 1998); secondly, a size that would reveal practicality, logistics, the uncertainty perceived in the study area,

¹⁸ There were only three sampling points from the DHS (2003) data covering my proposed study area.

¹⁹ The expected sample size without non-response contingency factor was estimated at 316, based on 40 to 71% prevalence rate information gathered from the WHO Lagos Office and applying a non-response factor of 60% to arrive at 505. More details are presented under the main study.

costs, scale development issues and derivation of high-quality parameter estimates (Mooney *et al.*, 1993; Hill, 1998; Johanson and Brooks, 2010); and thirdly, a size that would accommodate the anticipated need for field assistants.

We piloted a sample of 51 questionnaires, guided by the above criteria; however, as none of the literature on sample sizes for pilot studies takes into consideration the use of field assistants, to achieve this balance, I adopted the following distribution quota: 30 questionnaires administered by the PhD researcher and 21 questionnaires administered by two field assistants. The division was based on minimum and maximum sample sizes of between 10 and 30, as recommended by Hill (1998), to allow the PhD researcher to gain the full knowledge and experience of the pilot study and contribute to questionnaire development. The additional sample of 21 was piloted by two field assistants²⁰ for questionnaire development and as part of the training for the main study phase (Campanelli *et al.*, 1991; Barriball and While, 1994; Hertzog, 2008).

4.6 Data Processing and Analysis of Pilot Study

Two main products emanated from the pilot study; transcripts from 18 semi-structured interviews and 49 out of 51 completed questionnaires. These were analysed for integration and improvement of research instruments used in the main study.

4.6.1 Analysing Semi-structured Interviews: Content Analysis

I employed content analysis to transcribe, analyse and interpret the semi-structured interviews, so that they were integrated in a quantitative form into the questionnaire survey (Weber, 1990; Bazeley, 2003). This posed as a flexible method using a set of self-developed procedures to interpret and quantify qualitative text, such as that generated in open-ended questions, but this process faced loss of information (White and Marsh, 2006).

The basic principle employed was that many words or phrases emanating from the transcripts of the interviews were classified under categories based on the similarity of their meanings. They included working environment, treatment-seeking and preventative behaviours, treatment choices, risky behaviours and activities, determinants of first treatment choice and belief. The texts were quantified to numeric frequencies, and high frequencies meant they were relevant to their particular categories. I developed new questions for the main questionnaire using the responses as

²⁰ The field assistants were being trained ahead of time to participate in the main study phase.

answer options in new questions, and where they were of low frequency, classified them as an “other” response option in the questionnaire. The approach treated qualitative data in a quantitative manner and generated themes in the interim results – documented in Appendix IX – that are used to contextualise place processes and explain multivariate relationships in Chapter Seven.

4.6.2 Analysing the Pilot Questionnaire Survey

The main reason behind piloting the questionnaire was to identify content and validity issues, as well as identify problematic questions. It was also to give an idea of the socio-demographic characteristics of the study population to guide the selection of a study sample during the main study. As this pilot questionnaire survey is not the main study, I analyse and present only interim results so as to give us background information on the accessibility rates and socio-economic groupings of the sample population as presented in Appendix IX.

4.7 Feedback from Pilot Study

This section documents the feedback and experiences from the pilot study likely to affect the main study. They include accessibility, non-responses, sensitive questions, social desirability, time constraints, and carrying out the work under the Eko Malaria Project.

4.7.1 Accessibility and Barriers

Eighty-eight households were visited for the pilot questionnaire survey; 51 participated, of which two dropped out because they found some questions too personal. Twenty households were approached for the semi-structured interview and 18 responded; there were no drop-outs. Households of a high socio-economic class mainly resided in gated communities that were often within mixed-income areas, making access to them generally difficult due to private, strict security services that spanned the area (see Appendix X). There was generally better access to medium and low socio-economic class households because most people lived an outdoors lifestyle, as referred to earlier (see Appendix V). Nigeria is a country with distinct ethnic groups that can often influence access to certain communities. Though Lagos state is a cosmopolitan urban area, this distinctness is maintained, often reflected in residential patterns such that access to these communities can be influenced by cultural preferences. Even though I had knowledge of Yoruba, the main language spoken in Western Nigeria and Lagos, from the pilot study I realised that the communities were more heterogeneous than I

imagined, and knowledge of Yoruba was not always enough to penetrate and work within some communities. There were also issues of timing and household availability; many working household heads/spouses were scarcely available for weekday interviews. These were major considerations, requiring the need to employ field assistants with diverse characteristics and flexibility.

4.7.2 Difficult and Sensitive Questions

A number of the participants had difficulties responding to questions on income and expenditure, housing characteristics, health status and service usage such that the participants were uncooperative or interviewers had to probe further. For example, questions pertaining to housing/economic characteristics: *“How much rent do you pay?”*, *“How much do you earn in wages?”*, *“What is the condition of your wall?”*, *“What is the condition of your roof?”*, *“Has anyone in your household experienced malaria last week or in the last year?”*, *“What health care facility do you use?”*, *“Any open drains?”*, etc. Some participants found them too personal, were put off by the questions, not willing to share the answers or did not know, just as Rutstein and Johnson (2004) noted when asking about the exact incomes of household members. This often led to incomplete questionnaires, non-responses to particular items and even social desirability issues. I recorded a 30% non-response rate for the questions on malaria occurrence and asset ownership a 32.7% non-response rate for the question for rent; 33% for that on land and property ownership; and 67.3% for that on income.

4.7.3 Working Under the Eko Free Malaria Project

Undertaking this research under the Eko Free Malaria Project had its positive and negative aspects. While it permitted me to undertake my pilot study in Lagos state and have access to data on malaria and relational variables, it sometimes had consequences for the way we were viewed during fieldwork. We had to give more explanations to clarify our status. This sometimes meant spending a longer time with each participant and could also have had consequences for the response rates of some of the questions posed from the questionnaire survey. However, it was still positive in providing local access into communities, and secondary data sources.

4.7.4 Political Context

One important observation noted during the pilot study was that the current government had ongoing projects (road expansion, development of public transport infrastructure and parks) as shown in Appendix XXII, some of which were carried out in Oshodi,

Ikeja and Kosofe LGAs. This meant that residents lost their homes. There was limited knowledge about which areas would be affected in the future, and as such, many communities were transient. There was a lot of uncertainty while planning for the main study. This local context affected the non-response factor to be incorporated in the final sample size and the need to use field assistants to ensure that the main study was completed in a shorter time than originally planned.

4.8 Secondary Data Sources

In this study, I gathered data on malaria infection, meteorological, entomological, GIS and remote sensing data from a range of governmental and non-governmental sources. As noted by White (2010), while data from these sources are extensively calibrated and robust due to the financial investment on the part of the institutions, they are often a subject of manipulation and collected at spatial scales that may not suit the researcher's needs. In this section, we discuss only the malaria infection and meteorological datasets. Others will be discussed separately.

4.8.1 Clinical Malaria Infection Data Collection

The Lagos State Ministry of Health's (LSMoH) health care facilities (HCFs) register, describing the reporting capabilities of all private and government facilities, revealed that only 25 government HCFs at secondary and tertiary levels had the capacity to gather and report data as shown in Figure 12. As this situation was confirmed by further fieldwork, I designed the data collection efforts to gather all monthly malaria infection data from these HCFs assigned to LGAs in Lagos state between 2000 and 2009 (Figure 12). The purpose was to use the data to identify LGAs with elevated malaria incidence rates that would form the focus of further investigations in this study. Incompleteness of data has consequences for robustness and true representation of disease levels. Such quality issues have been encountered by Chilundo *et al.* (2004) in Mozambique.

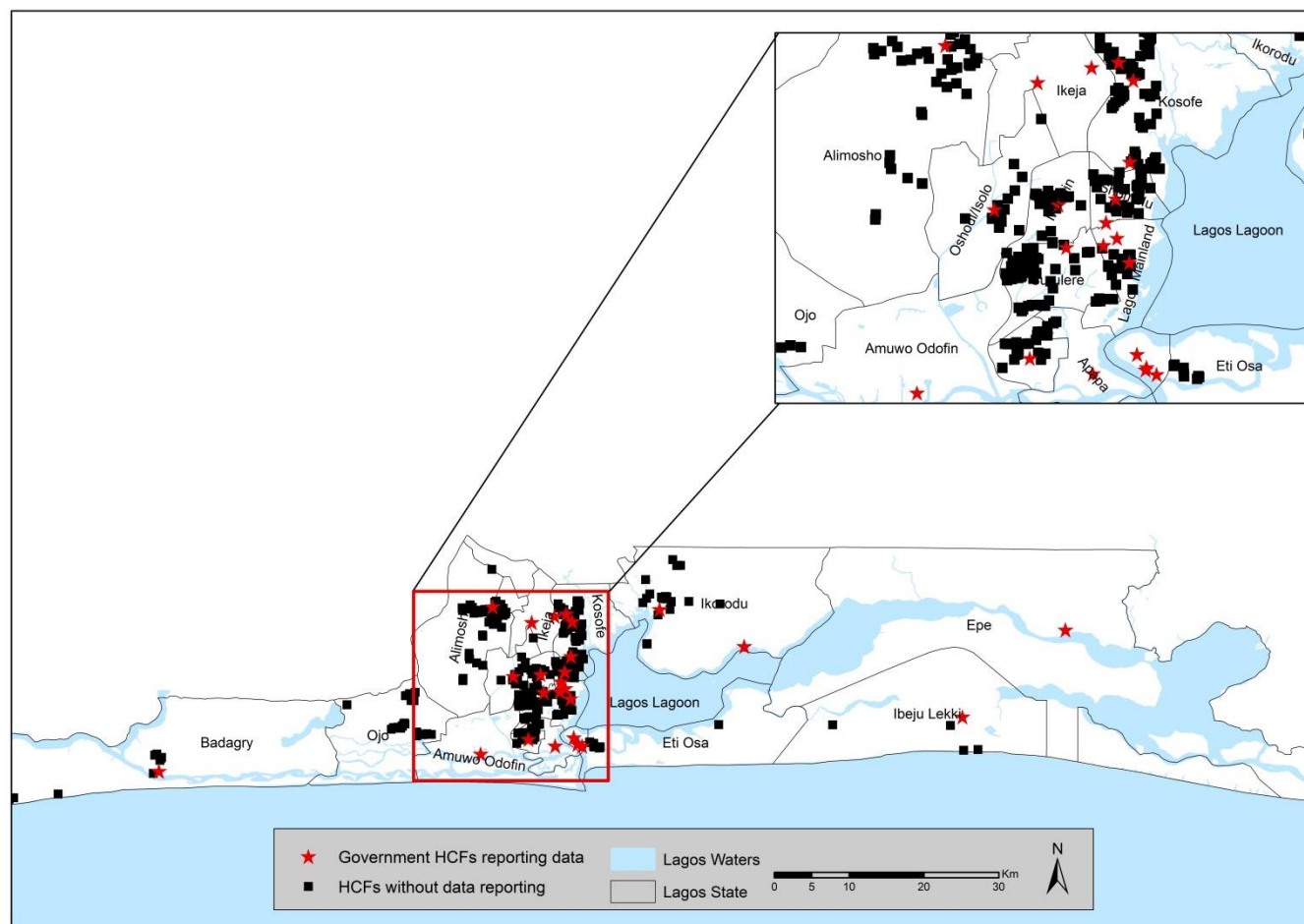


Figure 12: Map showing all HCFs in Lagos state

4.8.1.1 Data Collection Strategy

I designed the data collection system to be based on all monthly malaria infection data (in and out patients) for all 25 HCFs for the period 2000–2009²¹. These were retrieved from their archived paper/file storage – not the sophisticated database reporting system used by health systems in developed countries (Klein and Bosman., 2005) – and abstracted manually using the data entry template I designed for this purpose. These are presented in Appendices XI and XII.

The data entry templates take into account the layout of the source material the International Classification of Diseases and Related Health Problems (ICD & RHP) register used by LSMoH, the precision level of malaria data available and the need to minimise data entry error.

Due to access restrictions to the data by the LSMoH, I worked in a team with two medical records officers assigned to me for the data abstraction exercise. They underwent one day's training on data entry expectations and standardisation to minimise errors and clarification.²² All data entry and clarification tasks were shared amongst the team. Often, though, the data abstracted was mostly aggregated, as reported by the HCF, and not as precise as the requirements of the template in Appendix XII.

There were consequences for data entry errors and a time delay using the hand copying approach (Gimbel *et al.*, 2011). As a quality control measure, I reviewed all ICD & HRP registers for inconsistencies in data reporting, and we performed spot checks of data copied between ourselves. Where inconsistencies arose in the data, we clarified them with senior members of staff and where necessary undertook a further clarification by visiting the HCF. Though we had quality checks in place to address entry errors, preliminary quality assessment showed that there were still many missing values from many HCFs; newly registered HCFs did not have data spanning the whole period from 2000 to 2009, limiting research on space-time patterns to only 14 HCFs out of the original 25 with data-reporting capacity, and data was often not as precise as the details in the templates. This data was subjected to further quality assessment, as described in the next section and presented in Chapter Five.²³

²¹ N.B There are only 25 HCFs with data reporting capability, the private HCFs do not have the capacity and are not mandated by law. Thus the focus is the 25 data reporting HCFs in LSMoH.

²² The training included how to use the data templates for data entry, dealing with missing data, zero values, cross checking, use of symbologies including dash signs, ascertaining non-occurrence of malaria and aggregate values.

²³ The quality of this data and reporting system is discussed in full details in the next chapter.

4.8.2 Collection of Malaria Infection Quality Indicator Data

During the malaria infection data abstraction, I gathered responses to theoretically relevant summary questions and performed tasks through two protocols, the systems assessment protocol (SAP) (Appendix XIII) and the data verification protocol (DVP) (Appendix XIV) adapted from the Global Fund to Fight Aids, Tuberculosis and Malaria data quality assessment strategy (GFATM, 2009). The approach focuses on assessing the system that generates the malaria data as well as the data itself. By the observation of work practices, review of existing documents including disease registers, and informal interviews with medical record officers, heads and staff at the secondary health care facilities, also known as service delivery sites (SDSs), and reporting units, we gathered information on nine quality indicators: accuracy, completeness, reliability, consistency, timeliness, confidentiality, precision, accessibility and availability. The interviewing and data-gathering processes were informal but focused everyday conversations and enquiries as employed by Chilundo *et al.* (2004) and the (GFATM, 2009). The idea was to respond to the set of summary questions from SAP and DVP. The effort to achieve this objective is discussed in details in Chapter five.

4.8.3 Meteorological Variables Data Collection

Data on meteorological variables, such as monthly data on total rainfall, mean monthly temperature and relative humidity, sunshine duration and number of rain days for 2000 to 2009 were gathered from the meteorological station in Ikeja Airport (meteorological station is shown in yellow in Figure 13; Ikeja/Kosofe study focus area in purple)²⁴ with the purposes of examining its relationship with malaria infection data obtained from reporting HCFs in Ikeja and Kosofe LGAs under multiple time-lag scenarios²⁵ (Ye *et al.*, 2008). As this data has been gathered in months it does not allow the consideration of shorter time-lags, such as nine or ten days, that are of greatest biological importance for the development and survival of the anopheles and parasites (Macdonald, 1957; Teklehaimanot *et al.*, 2004).

4.9 Data Processing and Analysis

This section is concerned with methods used in the processing and analysis of malaria infection and climate data towards the achievement of the research objectives.

²⁴ Ikeja meteorological station is the only station generating climate data for the study area.

²⁵ There are significant climatic variations across Lagos state as well as data quality issues with climate and malaria data, including that of scale, which would affect the outcome when data is averaged and explored on a state-wide basis. To address these, I have therefore focused on Ikeja and Kosofe LGAs, which do not only have complete and reliable datasets for malaria from their HCFs but also a local meteorological station as a location of interest for this research work.

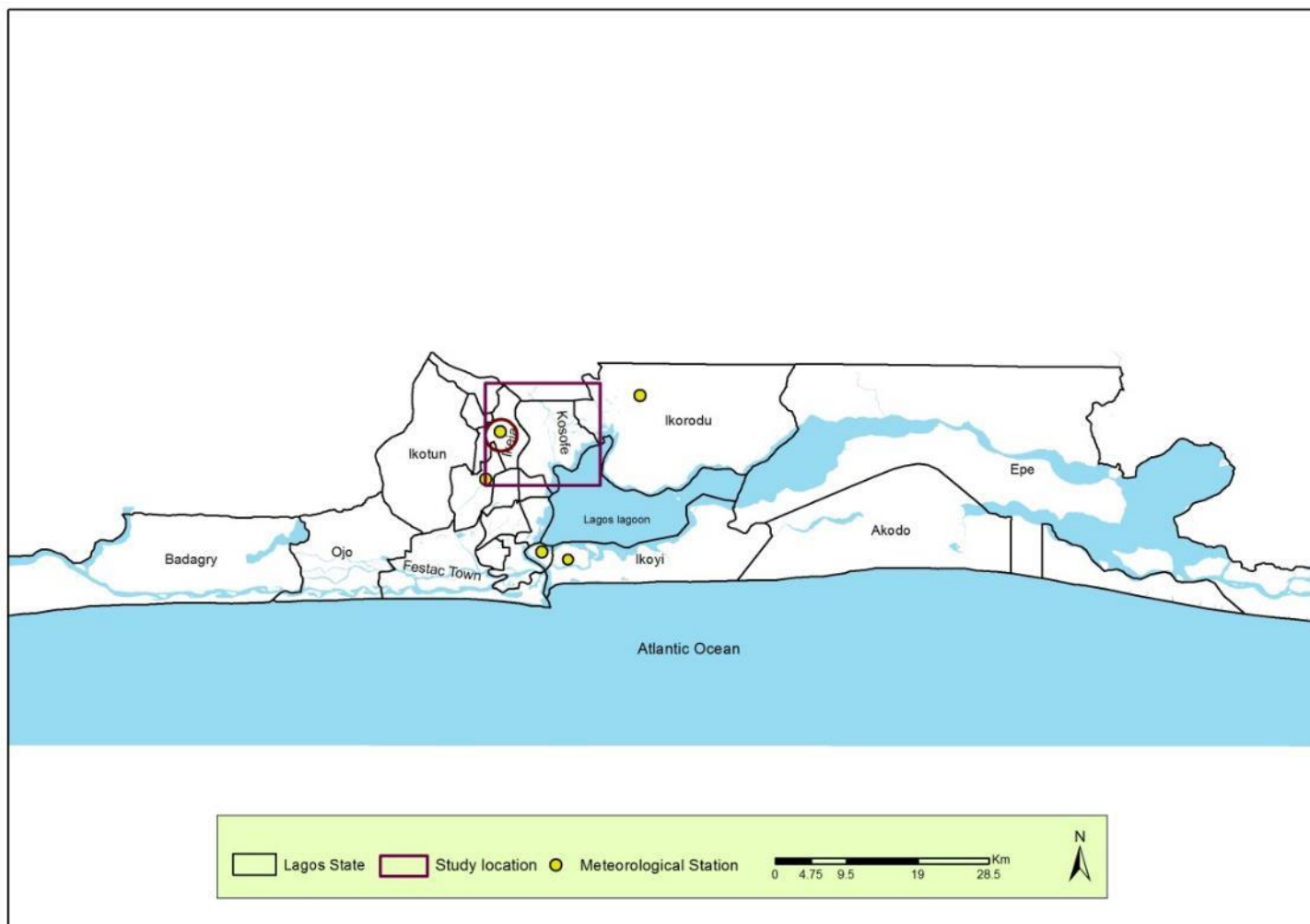


Figure 13: Distribution of meteorological stations in the study area

4.9.1 Exploration and Visualisation of Space-Time Patterns of Malaria Infection

As a first step, all malaria infection data from the HCFs were reviewed, updated for missing values where possible, integrated and joined with the unique IDs of the HCF spatial database within the ESRI ArcGIS 10.1 software. I explored and detected space-time patterns from the resulting spatio-temporal database using GeoTIME software.

I used GeoTIME software which utilises a density-based algorithm to detect elevated disease incidence rates in georeferenced malaria-infection time-series data. The algorithm is flexible and can work without specifying an *a priori* cluster threshold, and where defined can be done in a non-probabilistic or non-statistical manner, unlike other statistical or model based approaches such as space-time scan statistics, Bayesian modelling (Kearns and Joseph, 1993; Robertson *et al.*, 2010; Cromley and McLafferty, 2012). It is this unique characteristic of visualising spatial and temporal patterns in one view and analysing trends in a non-probabilistic manner in one interface that makes it different from other spatial only (e.g spatial autocorrelation) or spatio-temporal methods (Oppong and Harold, 2009) mentioned earlier and thus, a choice for this thesis. This non-probabilistic approach, though suitable for the exploratory aim of this thesis, cannot statistically verify areas identified as having elevated disease incidence, particularly where large differences in distances and densities occur in the datasets. This is mediated by defining multiple density thresholds according to the characteristics of the data.

4.9.1.1 Space-Time Clustering Criteria Process in GeoTIME

To examine space time clustering in GeoTIME, we may or may not define a priori density criteria as noted in the section before. Where we do not define *a priori*, the software reads and understands your data to detect likely clusters.

Due to the nature of my data which is characterised by high and low values as well as missing data, that are likely to lead to unstable results, I chose to predefine multiple density thresholds based on the characteristics of my data. In this case, I define a threshold in terms of number of cases (here derived as the incidence rate), temporal search axis and the spatial extent. I derived incidence rate using the formula:

$$\text{Incidence rate per 1000} = \frac{\text{Number of new cases per given month}}{\text{Population size at risk per given month}} \times 1000$$

Source: Boyle and Parkin (1991)

Equation 2: Formula for incidence rate

Where:

- Number of new cases: Number of malaria cases per HCF per month
- Population size at risk: Total number of patients visiting the HCFs per month

In the absence of appropriate population-at-risk data, I standardised the number of malaria cases reported at these HCFs (numerator) using the total number of patient visitors per month per health care facility as denominator as used by Gething *et al.* (2006) under similar circumstances. This accommodates small-number problems so that HCFs and LGAs with few patient visitors are not ignored in the analysis. In doing this, I derived values for monthly malaria incidence rate using Equation 2.

While some studies state 1 in 10,000 (0.1 per 1000) cases of malaria per annum as a situation of stable malaria transmission²⁶, or 1 in 1000 for malaria-endemic areas of which Nigeria is part (Snow et al., 2008; WHO, 2012a), I have found these still too low for Lagos, where transmission is high all year round. According to the WHO (2006), there is yet to be a criterion set for differentiating levels of malaria transmission intensity; therefore, I explore the summary statistics (mean, median and upper inter quartile range value) of the malaria incidence rates to arrive at three rates that likely depict the true incidence level in the study location.

I derived median, average and upper quartile incidence rates across the period 2000 to 2009 for each HCF. I found the average across HCFs for each of these summary statistics to arrive at a median standardised malaria incidence rate (42 per 1000); secondly, the average rate (71 per 1000); and thirdly, the upper quartile rate (180 per 1000 as highest). I utilised these rates as a benchmark to identify HCFs that report within and above it.

For time definition, I extended the search to search for infection rates (42, 71 and 180 per 1000) that occur in five consecutive months during the period 2000–2009 such that any HCF showing this trend will be targeted. I have employed five months based on the time period for stable malaria as defined by Craig *et al.* (1999) to depict minimum period to characterise regions with stable malaria transmission. I defined a distance of 10km based on the outcome of exploring the HCFs spatial extent and study-area coverage such that the focus is on the HCFs in urban centres. HCFs serving peripheral or what are called peri-urban, locations such as Ikorodu, Epe, Badagry and Ibeju Lekki

²⁶ Under stable malaria transmission, malaria is endemic and occurs in high levels across seasons.

LGAs are excluded from the analysis. The strategy searches for the defined infection rates in any consecutive blocks of data in 5 months across 120 months (year 2000 to 2009). What this means is that it searches for the occurrence of malaria up and above defined incidence rates (thresholds) in any consecutive 5 months across 120 months irrespective of when it occurs for each HCF. As long as a HCF has shown a particular threshold figure in any of the five consecutive months, this will be detected by the software. For example 5 months' time period may occur between June and December 2007 in HCF 1 while in another March to August 2001 in another and October 2002 to March 2003 for another etc. The flexibility of using 5 months accommodates the extremes of missing data such that analysis is applied on consecutively occurring datasets of 5 months minimum irrespective of when the 5 months occur in the datasets of 120 months.

The results of this effort presented in 2D and 3D using GeoTIME geovisualisation methodology using space and time interfaces is shown in Chapter Six. The size of a symbology reflects the incidence of clinical malaria infection per month per HCF. The areas with HCFs with an elevated incidence of 180 per 1000 and above are selected in order to be further considered, together with their ecological characteristics.

It is important at this time to point out that the datasets available for this research are limited in spatial and temporal coverage in several ways. Firstly, the availability of data had consequences such that the geographic location of clinical malaria observations were recorded only at the place of reporting and not the place of occurrence, meaning these data are not tied to or related to the residences of patients who visit the HCF. Secondly, it is not sample data but data available for government HCFs with data-reporting capability in Lagos state covering the years 2000 to 2009 and this does not include private HCFs or newly registered HCF. Thirdly, this dataset is characterised by missing values, and as a result, incidence rates for certain months can be missed but the criteria definition used in this analysis only selects clustering limits that occur in five consecutive months which do not necessarily have to be same time for all HCFs and thus minimising this effect. These limitations in my datasets had consequences such that the results produced may not be generalisable. This exploratory stage of the thesis to select a study area for in-depth study is presented in Chapter Six.

4.9.2 The Relationship between Malaria and Meteorological Variables

Across the literature, there has not been a consensus on the most valuable representation of climate condition, as studies have used mean, minimum and maximum measures of the meteorological variables derived daily, weekly, monthly, seasonally and even annually (Craig *et al.*, 2004b; Ye *et al.*, 2008; Oluleye and Akinbobola, 2010; Tay *et al.*, 2012) and assessed its indirect impact on a range of malariometric indices. In these studies, both statistically significant and non-significant relationships have been recorded. Meaning significant seasonal variation in malaria induced by seasonal changes has occurred in some study instances with the type of measure utilised.

In this research, I have thus exploited the indirect relation between meteorological variables and malariometric indices, as Ye *et al.* (2008) and Zhang *et al.* (2010) have done, to assess and identify significant associations. Precisely, I focus on monthly clinical malaria infection data from the HCF in Ikeja and Kosofe LGAs and monthly meteorological variables: mean monthly temperature and total monthly rainfall (Ye *et al.*, 2008; Li *et al.*, 2013); monthly average relative humidity (Zhang *et al.*, 2010; Li *et al.*, 2013); total monthly hours of sunshine (Akinbobola and Omotosho, 2011; Li *et al.*, 2013) and number of rain days (Akhtar and McMichael, 1996; Patz *et al.*, 2003) where statistically significant relationships with malaria have been found with seasonal changes in climate despite the locations having thresholds climatic conditions that sustain vector survival and thus abundance. The studies by Ye *et al.* (2008) and Tay *et al.* (2012) showed that even with climatic conditions being constantly above threshold needed for vector survival, the statistical significances of the relationships continued to change from the point of optimum climatic condition to the point where climatic conditions are least suitable for vector survival and possibly malaria incidence.

The meteorological variables were obtained from the station at Ikeja International Airport (see Figure 13), cleansed and then processed into appropriate databases. This location was selected as an area for further in-depth analysis based partly on the preliminary findings from exploring locations where HCFs reported elevated malaria incidence rates over space and time (see Chapter Six for details).

As an initial step, I defined four time-lags restricted by the monthly temporal resolution of the clinical and climate datasets. Time-lags are important because they model the time required for climate to settle in and impact on the anopheles mosquito and parasite in the way described next. During this time period the following may happen: climate

may have an effect on anopheles, human bite and possibly translate to malaria where human behaviour permits. For example, under an appropriate temperature (16 to 35°C) (Macdonald, 1957; Craig *et al.*, 1999; Service and Townson, 2002), the right amount of rainfall (80–100mm) (Craig *et al.*, 1999; Ye *et al.*, 2008) and intensity and relative humidity (at least 60%) (Craig *et al.*, 1999; Ye *et al.*, 2008) create suitable breeding habitats, which determine the duration of the life-cycle and in turn the abundance of the vector during an appropriate time lag. The time-lags utilised are no time-lag, and one month's, two months' and three months' time-lags modelled as periods required for the mosquito life-cycle, parasite development, time from adult first bite to time of infectious bite, and incubation period in a human host under conditions where optimal temperature of 28°C is assumed to occur as similar to temperature conditions and seasonal variations that often occurs at certain times in my study area as effectively applied and tested by Craig *et al.* (2004b), Teklehaimanot *et al.* (2004) and Zhang *et al.* (2010) to accommodate ad model climatic conditions that sustain vector habitats, their abundance, and thus implications for disease spread in similar ecological conditions.

Firstly, I applied descriptive statistics to summarise the meteorological and malaria datasets, I then used graphs to depict patterns and qualitatively describe trends in both datasets without quantification (Field, 2010). Thirdly, I conducted a time-lagged correlation analysis between meteorological variables and clinical malaria as used by Zhang *et al.* (2010) in similar research. I used SPSS version 21 analytics software to undertake these analyses.

4.10 Main Study

The focus of this section is to describe efforts used to gather data on urban malaria risks in a cross-section of households in the Ikeja and Kosofe LGAs between June and October 2010. The location selected for in-depth studies has been described earlier and the mode of selection is presented in Chapter Six.

The research design is theoretically based on the human ecology of disease and I have translated the facets of the framework into two broad classes of behavioural and environmental variables (built and physical), as shown in Figure 8 (Chapter Three), with household as a study unit to represent population, and health represented by the occurrence of malaria. The hypothesised variables are further broken down in Table 3.

A number of risk variables emerged from the review of literature and knowledge of the case study location to be tested in my study and there are presented in Table 3 showing

the direction of relationship with malaria. According to the literature review, occupation, religion, animal presence, room density, condition of wall have had both a positive and negative impact while wealth, education of head of household, preventative behaviour and household size also have reported a positive and negative influence and in some instances studies reported that these variables did in fact not have any impact at all on malaria. Other risk factors like being a vulnerable person (pregnant women, children and non-immune travellers), proximity to urban agriculture, presence of stagnant water and vegetation, water storage and NDVI are associated with increasing malaria risks and are hypothesized to follow similar directions in this research. Topographic characteristics like elevation from literature are inversely related to malaria but in areas with diverse topographic characteristics. The higher the elevation, the lower the risk of malaria and this is same direction with slope as the greater the slope the less the potential for malaria breakout. In lowland areas, just like my study location they are non significant. However, I find it useful to examine elevation given that it has not been examined in an urban location and areas with elevation below sea level as well as slope as this is suggested to be more suitable for low lying areas.

From my knowledge of Lagos state, I note that working at night including participating with social activities and the condition of mosquito protection are important risk conditions that can lead to a household being infected with malaria. I also note ethnic tribes residing in Lagos which has not been examined in any of the literature reviewed. This is because I suspect that some tribes like the Aworis who site their homes beside open water (a confirmed vector breeding habitat) may be susceptible to malaria.

Even though some variables mentioned earlier are inconclusive about the direction of relationship with malaria due to the often mixed impacts recorded. I still consider them in my thesis by explaining and exploring them to be important in creating knowledge on the ecology of urban malaria and also of this location, given the limited knowledge on it. Through this, I identify important variables to further the understanding of the disease in this location. I develop research instruments to gather data that represent them so as to explore as well as confirm their empirical relationships with the burden of malaria on households.

Table 3: Risk of malaria in households and their independent risk variables

		<i>Risk Factor</i>	<i>Definition of Measure and Indicator as used in Analysis</i>	<i>Reference</i>	<i>Direction of Relationship</i>
Dependent variable	Risk of malaria in household	Risk of malaria in household	Occurrence of malaria or febrile illness for any member of the household in the last year	Afrane <i>et al.</i> (2004)	Not applicable
Independent Risk Variables	Behavioural (Socio-cultural Environment)	Occupation	Rank of occupation of head of household	Yapabandara and Curtis (2004); Peterson <i>et al.</i> (2009);	↑ ↓
		Occupational exposure	Household with adults working at night without mosquito protection	Ferreira <i>et al.</i> (2012); field work	FW
		Wealth	Wealth index based on assets ownership	Baragatti <i>et al.</i> (2009)	↑ ↓ NS
		Education	Level of education of head of household	Keating <i>et al.</i> (2005)	↑ ↓ NS
		Ethnicity	Tribal class and main language spoken	Okwa (2003); Ye <i>et al.</i> (2008); Phillips <i>et al.</i> (2009); Peters (2010)	↑
		Religion	Religion practised in household	Peters (2010); Oresanya (2008)	↓
		Preventative behaviour	Usage of window and door mosquito net, actual usage of ITN the night before the interview and use of insecticide/pesticides	Njama <i>et al.</i> (2003); Saeed and Ahmed (2003a); Alemu <i>et al.</i> (2011)	↓ NS
		Level of knowledge	Knowledge of symptoms, knowledge of cause	Njama <i>et al.</i> (2003); Saeed and Ahmed (2003a); Alemu <i>et al.</i> (2011)	↓ NS
		Household vulnerability	Occurrence of child aged five and below in household	WHO (2012a); Peterson <i>et al.</i> (2009)	↑
		Belief	Occurrence of a belief factor	Saeed and Ahmed (2003a); Peters (2010)	NS
		Travel History	Travel to rural area in the last year by any household member	Meade (1977); Ng'andu <i>et al.</i> (1989); Baragatti <i>et al.</i> (2009)	↑
		Agriculture	Proximity to urban farmlands and animal husbandry	Afrane <i>et al.</i> (2004); Klinkenberg <i>et al.</i> (2005)	↑
	Environment (Built)	Place of residence	Residing in either Ikeja or Kosofe LGA	Ye <i>et al.</i> (2008)	NS
		Room density	Number of persons per room in house	Clark <i>et al.</i> (2008); Ayele <i>et al.</i> (2012)	↑ ↓
		Housing characteristics	Condition of wall	Peterson <i>et al.</i> (2009); Ye <i>et al.</i> (2008); Deressa <i>et al.</i> (2007); field work	↓
			Condition of mosquito protection (door and window net)		FW
		Homestead risks	Open drains with water	Peterson <i>et al.</i> (2009)	↑
			Presence of bushes, grass, gardens and farmland (any vegetation)		↑
		Water storage	Storing water in the house	Matthys <i>et al.</i> (2006b)	↑
		Household size	Number of persons in household	Alemu <i>et al.</i> (2011); Ernst <i>et al.</i> (2009); Siri <i>et al.</i> (2010)	↑ ↓ NS
		Animal presence	Presence of livestock or domesticated animal	Yamamoto <i>et al.</i> (2009); Siri <i>et al.</i> (2010)	↑ ↓
	Environment (Physical)	Vegetation cover and Climate	Mean Normalised Difference Vegetation Index (NDVI) value within 200m buffer of household location	Machault <i>et al.</i> (2010)	↑
		Water bodies	Proximity to open water bodies	Peterson <i>et al.</i> (2009)	↓
		Mosquito vector habitat locations	Proximity to vector habitat	Machault <i>et al.</i> (2010)	↓
		Topographic characteristics	Mean elevation value within 200m buffer of household location	Myers <i>et al.</i> (2009); Cohen <i>et al.</i> (2010); Nmor <i>et al.</i> (2013)	↓ NS
			Slope value within 200m buffer of household location		↓ NS

NS: Non-significant FW: Fieldwork ↑: Positive ↓: Negative

I used a questionnaire survey, direct observation protocol, GIS and remote sensing methods to gather these data on health, population, behavioural and environmental variables from a sample of households (Eisele *et al.*, 2003; Ye *et al.*, 2008; Machault *et al.*, 2010; Krefis *et al.*, 2011). During the data collection, the GPS coordinates of each household interviewed and agriculture locations was obtained using an Etrex Garmin GPS receiver (Ye *et al.*, 2008). Each household was given a unique identifier synonymous to the identifier used to store the geographic coordinate in the GPS receiver (Ye *et al.*, 2008).

4.10.1 Preparatory Phase and Implementation of Pilot Study Feedback

Flexibility has been cited often as the watch word in development research just because of the often unpredictable circumstances that may arise when working in sensitive areas or under political instability in developing countries (Nash, 2000; Scott *et al.*, 2006; Scheyvens, 2014). Based on the experience from the pilot study and experiences of Scott *et al.* (2006) in doing development field work, I noted and implemented some improvements. Particularly, I was open to flexibility and the need to adjust my strategies as the fieldwork progressed and where needed.

As this main study is a much larger project, I requested ethical clearance from the Federal Ministry of Health (FMoH) under the National Health Research Ethics Committee of Nigeria (NHREC) (see Appendix XV). I also obtained ethical clearance from Newcastle University (see Appendix XVI). I sought additional permission from the local community and traditional leaders (Baales, Chiefs, Obas) to undertake the household survey in their local communities.

I developed the direct observation protocol (see Appendix XVII) as a new research instrument following the reaction to questions on housing characteristics and conditions in the pilot study and literature such as Ye *et al.* (2008), Githinji (2009) and Yamamoto *et al.* (2010). It is used as a guide to directly observe the conditions of building walls, roofs, mosquito protection and environmental conditions in each household in a structured and consistent manner. The information gathered is dichotomous in nature on the presence or absence of various housing quality and environmental characteristics used to represent the built environment.

I improved on the questionnaire in a number of ways. I developed new questions from the results of the semi-structured interviews and local experiences pertaining to treatment-seeking behaviours and their influences, preventative behaviours, beliefs,

treatment types, risky behaviours and habits generated by predetermined categories and new ones formed through content analysis as described earlier. I used the qualitative responses to create new quantitative close-ended questions with answer options (Tang *et al.*, 1995). Others include details on pregnant women and non-immune travellers, travel patterns and the participants' contact details. I improved question layout and wordings, added new questions, eliminated irrelevant ones, added quality checks and additional instructions. For example I eliminated assets such as bicycles and grinders and added use of security guards and foreign summer holidays identified to be of local relevance to define wealth.

The experiences from the pilot study re-affirmed the need to use more field assistants for the following reasons. I noted the time required to complete a questionnaire (30 to 45 minutes); the complexity of the questions, the need to probe in some circumstances and poor literacy rates, despite being an urban location (see Table 2);²⁷ the complex sampling design that would be used in the absence of an exhaustive list of households; the need to enlist cooperation and overcome unfamiliarity shown by participants in research issues and interviews in Nigeria, as noted by Peil *et al.* (1982). I also noted the need to minimise workload for the proposed sample of 505 households and, in turn, interviewers' errors (Fowler, 2009), particularly in order to overcome some of the difficulties anticipated in the main study such as working under the constraints of time, health and safety and political context, which were additional controlling factors; to respond to language barrier and cultural sensitivity issues; and the execution of a multi-method household survey involving questionnaires, GPS mapping and direct observation data collection methods.

To minimise access issues in working households I ensured that data collection would be carried out during weekdays and weekends; and in the gated communities, we employed local help and where necessary I visited these areas personally. Though the main target was heads of households/spouses I bore in mind that it might not always be easy to reach them and in their absence we interviewed an alternative adult (over 18 years) in the household.

I also sourced georeferenced entomological data from multiple online sources to be verified during the main study. I obtained GIS data sets (water bodies and

²⁷ It was also important to maintain their use as over 33% of the population have limited education, with up to 15% not able to read and write a complete sentence.

administrative boundaries) from secondary sources (Geography Department, University of Lagos; National Population Commission, Lagos and Geoconnexions Ikeja, Lagos).

In summary, the benefits that ensued from undertaking a pilot study included creation of new knowledge from the semi-structured interviews, identification of logistics needs for the main study, development of new research instruments, improvement of the questionnaire survey, addressing access issues, development of sampling framework and strategy and re-assessing sample size estimates while accommodating uncertainties that might affect questionnaire response rates.

4.10.2 Questionnaire Survey

The weakness of the most recent DHS (2008) datasets, noted in an earlier version, still prevails, and thus there was still a need to employ a questionnaire survey. The questionnaire was drawn from a number of sources noted earlier in the literature review as well as Okafor and Odeyemi (2009), semi-structured interviews and experiences from fieldwork. The questionnaire remains the paper based interviewer administered questionnaire just as in the pilot study but only an improved version which implements feedback from pilot study and uses an improved map sampling framework developed for the main study. The interview took place at their place of residence and the focus is on the study population living within Ikeja and Kosofe LGAs just as described earlier in the pilot study.

The major questions that emerge in the improved questionnaire are used to measure behavioural variables listed in Table 3. They relate to level of knowledge, belief, preventative behaviours, ethnicity and religion, travel history, occupation and educational status of heads/spouses of household, household membership and socio-demographics, usage of and access to health care facilities and historical occurrence of malaria.

The ownership of assets, housing ownership, presence of amenities and basic infrastructure are used to derive wealth indices. According to Rutstein and Johnson (2004) and Filmer (2005), it is a more permanent way of representing household economic status, requiring only a single participant and fewer questions compared to the income or expenditure approach.

The questions on working environment are to depict exposure characteristics associated with the working environments of household members. They include job shifts,

geographic location, working place conditions and protective measures as revealed in the semi-structured interviews in the pilot study and currently integrated in the improved questionnaire survey.

The final section concludes with a “thank you” note and asks for contact details to send out the report of the study to interested participants and for further correspondence if required. The full details of questions to be asked with the aid of field assistants are presented in Appendix XVIII.

4.10.3 Recruitment, Selection and Training of Field Assistants

Based on the need for additional support for the main study as stated earlier, I recruited 12 field assistants of both genders with a minimum of secondary school qualification, a credit pass in English language with good reading and writing skills, knowledge of at least one of the main Nigerian languages and working knowledge of another, knowledge of Pidgin English,²⁸ are of different religions and ethnicities and with local knowledge of the communities. These field assistants were recommended by colleagues at the Geography Department, University of Lagos.

The field assistants underwent five days training which consisted of theory, role play, use of GPS and maps, health and safety in the field, actual data collection practice and feedback sessions (Campanelli *et al.*, 1991; Barriball and While, 1994; Fowler, 2009; Abate *et al.*, 2013). However, it is suggested that the use of multiple interviewers will introduce its own errors (Bailar *et al.*, 1977; May, 1989); but where a large number of questionnaires are involved, that can give rise to fatigue, and Fowler (2009) recommends that reducing the average interviewer’s workload and providing them with proper training and supervision is better than using few interviewers and a cost-effective way of increasing the precision of survey estimates. Snow *et al.*, (2008) and Kearns and Joseph (1993) demonstrated increases in the standard error of 14% to 41% arising from the increased workload per interviewer from 31 to 50 assignments. This, as noted by Fowler (2009), is a highly underappreciated aspect of survey design. Therefore, the training was held in an effort to provide interviewers with a uniform way of interpreting and asking questions, recording answers, observing environmental features, and providing information to participants about the survey, as well as enlisting, motivating and probing participants, as recommended by Campanelli *et al.* (1991); Barriball and While (1994); and Fowler (2009), as a way to reduce interviewer-associated errors.

²⁸ Pidgin English is a variant of the English language spoken locally in Nigeria.

The pre-testing of the improved questionnaire from the pilot study and direct observation protocol featured as part of the training. The field assistants were asked for feedback on difficult questions from the pre-testing and actual data collection practice to improve on the questionnaire (Campanelli *et al.*, 1991). They were further interviewed on the contents of the training, and at the end of the training exercise, only ten field assistants were recruited from the 12 that participated in the training. The ten field assistants were divided into pairs and while one did the interview the other accompanied. Thus in all there were five interviewers (including the PhD researcher and two assistants who had undertaken the pilot study) and another five escorts²⁹ (Khan *et al.*, 2011).

The final set of field assistants were made up of a mix of final-year university students, first degree holders, teachers and postgraduate students. They demonstrated full understanding of the data collection procedures, importance of response rates and the need to effectively enlist participation even though the survey was voluntary; they expressed their availability, flexibility, and willingness to participate throughout the data collection exercise and had appropriate educational qualifications to carry them through the exercise.

I supervised fieldwork, asked for daily feedback, reviewed returned questionnaires every two days and where possible followed up on incomplete questionnaires (Fowler, 2009; Alemu *et al.*, 2011). I re-certified the field assistants every two days, and I re-interviewed 20% of the participants to ensure agreement and improve consistency in the interpretation of questions (Gisev *et al.*, 2013). Our meeting points were at Maryland in Ikeja LGA and at Ketu in Kosofe LGA. Our modes of transport within and between localities were personal cars, the public bus, canoes, ferries, motorcycles and on foot.

4.10.4 Sample Size

While appropriate population data to determine sample size on my study site has been lacking,³⁰ similar studies have often not been transparent about the sample size derivation method in such a way as to use their guidelines (Yamane, 1967; Israel, 1992). To overcome these limitations, I applied Cochran's (1963) sample proportion formula (see Equation 3) using malaria prevalence rates from a number of study populations in

²⁹ There were only five interviewers, inclusive of the PhD researcher, and one escort per interviewer for the questionnaire survey. They needed to work in pairs for health and safety purposes.

³⁰ For the population-based sample size calculation method, the ideal would be to know the population size of each locality to understand variability to derive a sample size, but the last population census for 2006 at the locality level is yet to be published and as at the period of the fieldwork only the population figure at LGA level was available.

Lagos and a 60% non-response contingency factor over Israel (1992) suggestion of 10–30%. Non response in this case means item non response (incomplete answers) i.e inability to complete a household survey that includes the questionnaire and the environmental investigation using direct observation such that there are missing responses to any of the questions for a household. This is to accommodate local context and predictions from the pilot study³¹ as suggested by Magnani (1999) and Naing *et al.* (2006). Being flexible and accommodating uncertainties under the political situation which I anticipated is often a source of incomplete datasets. This is an important attribute as cited often by scholars like Nash (2000), Scott *et al.* (2006) and Scheyvens (2014) and it is important to accommodate this during initial sample size calculation.

By applying minimum and maximum prevalence rates of 7.7% in pregnant women (Agomo *et al.*, 2009) and 40 to 71% (WHO Office Representative, 2008)³² in Equation 3, I arrived at minimum and maximum figures of 109 and 316.

$$n = \frac{z^2(p * q)}{d^2}$$

Equation 3: Formula for sample size calculation based on prevalence rate

Source: Cochran (1963)

Where

- *n*= required sample size
- *z*= critical values of the standard normal distribution at the 5% level (1.96)
- *p*= proportion of people with malaria (prevalence)
- *q*= proportion of people without malaria (1-*p*)
- *d*= precision or acceptance range of error in estimating the risks of malaria (set at 5% or 0.05)

Minimum possible sample size (at 7.7% prevalence) = 109

Maximum possible sample size (at 40 to 71% prevalence) = 316

I have then applied a 60% item non-response contingency factor according to Equation 4 on the earlier calculated minimum sample sizes (109 to 316) derived using 40 to 71% prevalence rates reported by the WHO office in Lagos. The use of item non response

³¹ While I accounted for non-response, I anticipated difficulties with cooperation as well as access to heads of households based on feedback from the pilot study.

³² Personal communication with the WHO Office representative in Lagos state

contingency over and above 30% has been suggested by Magnani (1999) and Naing *et al.* (2006) for unpredictable local circumstances.

$$N = n + (n \cdot iNRCF)$$

Equation 4: Formula for estimated sample size for non-response contingency factor

Where

- N = final sample size
- n = sample size estimated from Equation 3
- $iNRCF$ = item non-response contingency factor of 60%

Final sample size (N) = 505

To achieve the minimum sample size, I need to enlist at least 505 households so that even with issues of item response, the sample size of completed questionnaires (i.e without item response) available for analysis should fall between 109 and 316. This means I will be working with a complete set of household datasets that will still be representative of the incidence in Lagos state. Only complete household cases will be finally used for analysis i.e those where item non response does not constitute the loss of a risk variable.

In order to enlist 505 households, I was flexible and employed a pragmatic approach to achieve this. I was aware there could be refusals to even participate as separate from item non response but unaware of how many refusals there would be. Therefore I periodically assessed progress during the fieldwork. I checked completeness of household survey (questionnaires and direct observation of household environment) to know when we are meeting the sample size requirement and re-strategize where necessary so that we still worked and administered the survey using the sampling strategy discussed next.

4.10.5 Study Population, Sampling Frameworks and Strategy

The study population remained the same as described in the pilot study and the main participants remained spouses/heads of households, but as they were often absent, as noted in the pilot study, we opted to interview any adult in the household above the age of 18 years. We did not carry out duplicate interviews in any household. To accommodate working households, the surveys were scheduled both at weekends and on weekdays. For health and safety reasons I scheduled we work within the hours of 8am and 6pm. We recruited our samples in similar manner as the pilot study interviews

and questionnaire surveys (see 4.4.1) but in this case we used an improved map sampling framework for which I gathered data on in the pilot study. We also used an interviewer administered paper based questionnaire described earlier in section 4.9.2.

We utilised a map sampling frame as suggested by Peil *et al.* (1982) and Siri *et al.* (2008) for use where exhaustive sampling frames presented a challenge, as is common in developing countries. Part of the sampling frame was developed in the pilot study and consisted of a list of supervisory and enumeration areas from the 2006 population census and two maps I developed. Though this was still not exhaustive, it was the best available, as conducting a census of the locality was not feasible given the time constraints (Howes *et al.*, 2006).

I developed the map sampling frameworks using data such as place names and coordinates of landmarks gathered in the pilot study, administrative boundaries and road network GIS data, and QuickBird fine resolution imagery sourced locally. I designed two map types for each of the 44 localities in Ikeja and Kosofe LGAs. The first map (Appendix XIX) shows the road network, random sampling points, and street and locality names with hand-drawn boundaries to emphasise the extent of the locality. The second map is an imagery map and (Appendix XX) shows land-use types deciphered from QuickBird fine resolution imagery, roads and the random sampling points. I used the QuickBird imagery map as a guide to the interpretation of land-use types, definition of built-up areas and elimination of swamp areas while using the locality map in Appendix XIX. Any random point that fell within a swamp area or any area suspected to fall into an office complex/market/industrial or rivers were further verified in the field and eliminated where necessary. A sample of the list of supervisory and enumeration areas³³ is presented in Appendix XXI³⁴ and they were used side by side with the maps in locating missing streets within the built-up areas. Even though the collection of maps and EAs are not as detailed as the sampling frames suggested by Parfitt (1997) to be most exhaustive, they were useful as a fieldwork guide, road guide, sampling guide and frame and container to facilitate fieldwork and guide the selection of my samples.³⁵

As Ikeja and Kosofe LGAs are a large diverse urban location, the sampling strategy is such that each of their 44 localities (see Figure 9, map insert) was given equal chances

³³ Supervisory areas (SA) are a set of enumeration areas, while enumeration areas are a set of streets.

³⁴ Due to restriction in data publication only a sample is presented.

³⁵ It was impossible to conduct a prior census of population of the study area due to limited resources.

to be investigated. I applied an area probability random sample design strategy (Fowler, 2009) using the locality maps (Appendix XIX) and distribution quota as presented in Table 4.

Table 4: Area Probability Sampling Strategy

	Probability of selection of localities at stage 1	Sample size of households selected in each locality at stage 2
Select all 44 localities and administer 9 to 12 questionnaires in each locality	1/1	9 to 12

Each locality was used as a frame to randomly select households where the questionnaire and direct observation would be administered. I used Hawth's random pre-selection sampling tool extension in ESRI ArcGIS software to create 505 random sample point locations (based on the estimated sample size that integrates item non response discussed earlier) at least 100m apart with approximately an equal number of samples within each of the 44 localities. The goal was to have as many attempts as possible (including refusals) so that the minimum household survey achieved is approximately and equally distributed across the localities and sum up to 505 which is the calculated sample size (Njama *et al.*, 2003). Approximately 9 to 12 random points fell inside each locality as noted in Table 4 but to achieve this, I needed to make a number of enlisting attempts accommodating possible refusals but this number is unknown because of the unpredictable local situation, the need to be flexible and pragmatic with the fieldwork and to respond locally as the need arises as suggested by Scott *et al.* (2006).

I hand sketched artificial boundaries around each randomly generated point location; this location, as shown in Appendix XIX, was used as a reference point to guide interviewers while in the field to approach households randomly and administer interviews where successful within each hand-drawn region (Eisele *et al.*, 2003). This accommodates refusals in the sense that any household that refused to participate the interviewer moves on to the next random household and still using the sampling framework. All random points that fell within swamps, rivers and areas without human habitation (e.g. industrial/commercial areas) were edited prior to data collection using the corresponding QuickBird imagery maps in Appendix XX or during data collection. The maps showing the output of the area probability sampling using the Hawth's sampling tool extension are shown as Appendices XIX and XX.

4.10.6 *Anopheles* Vector Breeding Habitats

My research lacks an entomological survey as part of the study and depends on anopheles breeding habitat data derived from surveys previously executed in Lagos, as applied similarly in Mauchault *et al.*'s (2010) study. Entomological surveys contain data the anopheles species types, occurrence and distribution of breeding and settling sites. In this study, I have obtained these from secondary sources such as the Mosquitomap data catalogue, the Malaria Entomological Profile of Nigeria from WHO AFRO region, the Mapping Malaria Risk in Africa (MARA) website and journal articles. When these data sources are collated they will be used to derive proximity measures to the habitat locations to contextualise household's physical environmental risks.

Mosquitomap is a geospatially referenced global data catalogue that hosts over 126,000 records of entomological data. It is located at <http://www.mosquitomap.org/dataportal.htm> and authored by Desmond Foley and Richard Wilkerson of Walter Reed Biosystematics Unit (WRBU), based in the Smithsonian Institution, Washington DC. The entomological data dates back to the early 19th century and is donated by individuals and organisations and submission by mosquito workers involved in ongoing mosquito surveillance. Other sources include museum species and literature. For each mosquito species, their mode and date of data collection and uncertainties about the exact geographic location where data collection was conducted are specified. The data is downloadable in geospatial format and its interface is shown in Figure 15. Lagos state is shown in the brown ellipse with the exact location of the entomological survey highlighted as red dots, while the blue buffers represent uncertainty about the geographic location.

The Mapping Malaria Risk in Africa (MARA) initiative and Malaria Entomological Profile of Nigeria reports data specifically for Sub-Saharan Africa and Nigeria respectively in georeferenced format. They are efforts by African scientists, and the data is available from WHO AFRO *et al.* (2010) and <http://www.mara.org.za/>. I extracted all the georeferenced data in entomological surveys and integrated it into a spatial dataset in ESRI ArcGIS software. In addition to the three data sources described earlier, I sourced additional data from journal articles such as Brieger *et al.* (2001); Awolola *et al.* (2002b); Awolola *et al.* (2005); Afolabi *et al.* (2006); Awolola *et al.* (2007a); Awolola *et al.* (2007b); Okwa *et al.* (2007); Okwa *et al.* (2009); and Okorie *et al.* (2011). Some of this data have only place names and I updated them with coordinates

with the aid of the Nigerian place names gazetteer and in the field as part of the main study.

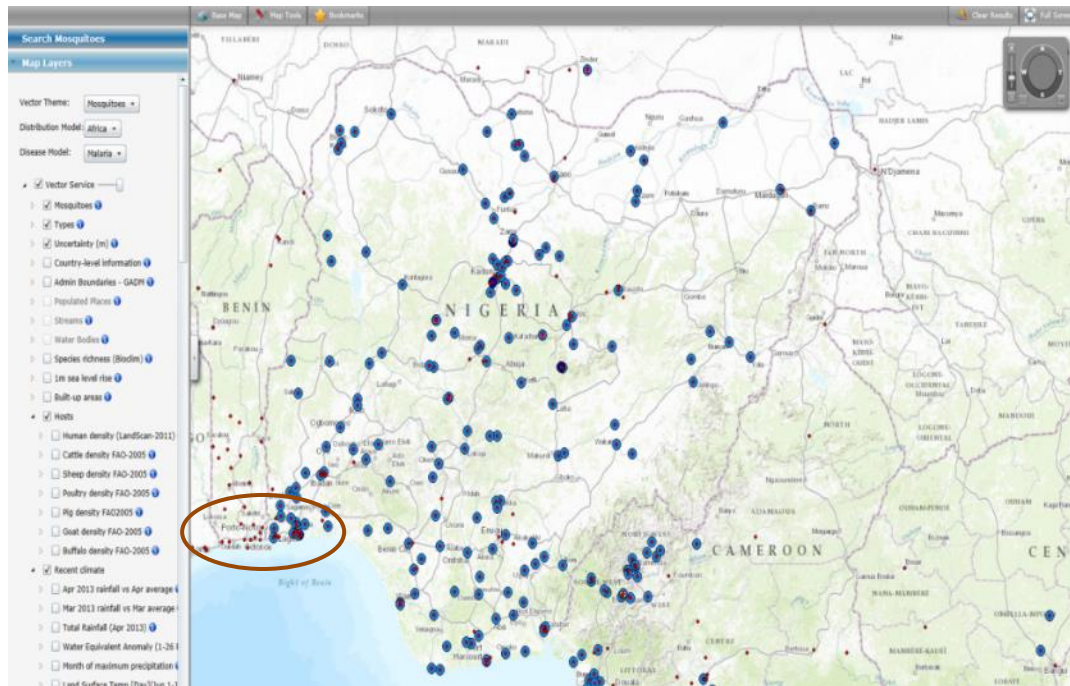


Figure 14: Mosquito map data catalogue interface

I collated and merged all secondary sources of entomology data into a spatial database using the ESRI ArcGIS software. I eliminated duplicates, verified original sources of data and extracted information specific only to Lagos state. The final output is presented as Figure 16. As the focus of this research is the Ikeja/Kosofe area, I further extracted data for the five locations that fell within the study area.

The weakness of this secondary-sourced data is that the surveys date as far back as 1951 and as such may not represent current vector habitat situations. I updated these locations and identified an additional three to represent unconfirmed habitats (shown in green in Figure 17) with the expert opinion from the Entomological Unit of the Nigerian Institute of Medical Research (NIMR). Unconfirmed breeding habitats are those where mosquitoes have been sited but without laboratory confirmation of their species types. The final output is presented in Figure 17, representing confirmed and unconfirmed presence of anopheles habitats. I derived proximity measures to vector breeding habitats using these resulting datasets and this process will be discussed in the next section.

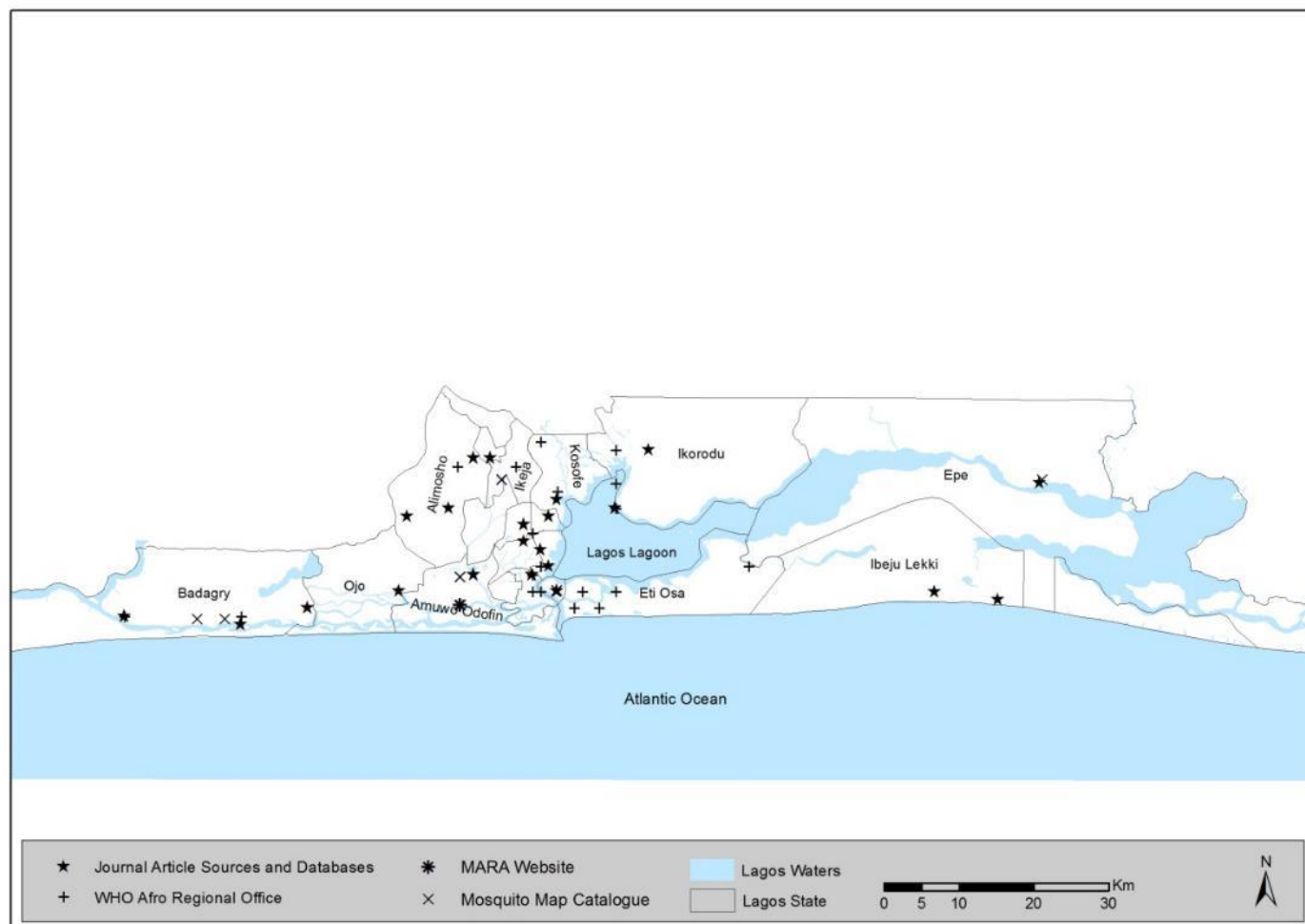


Figure 15: Collated entomological data for Lagos state

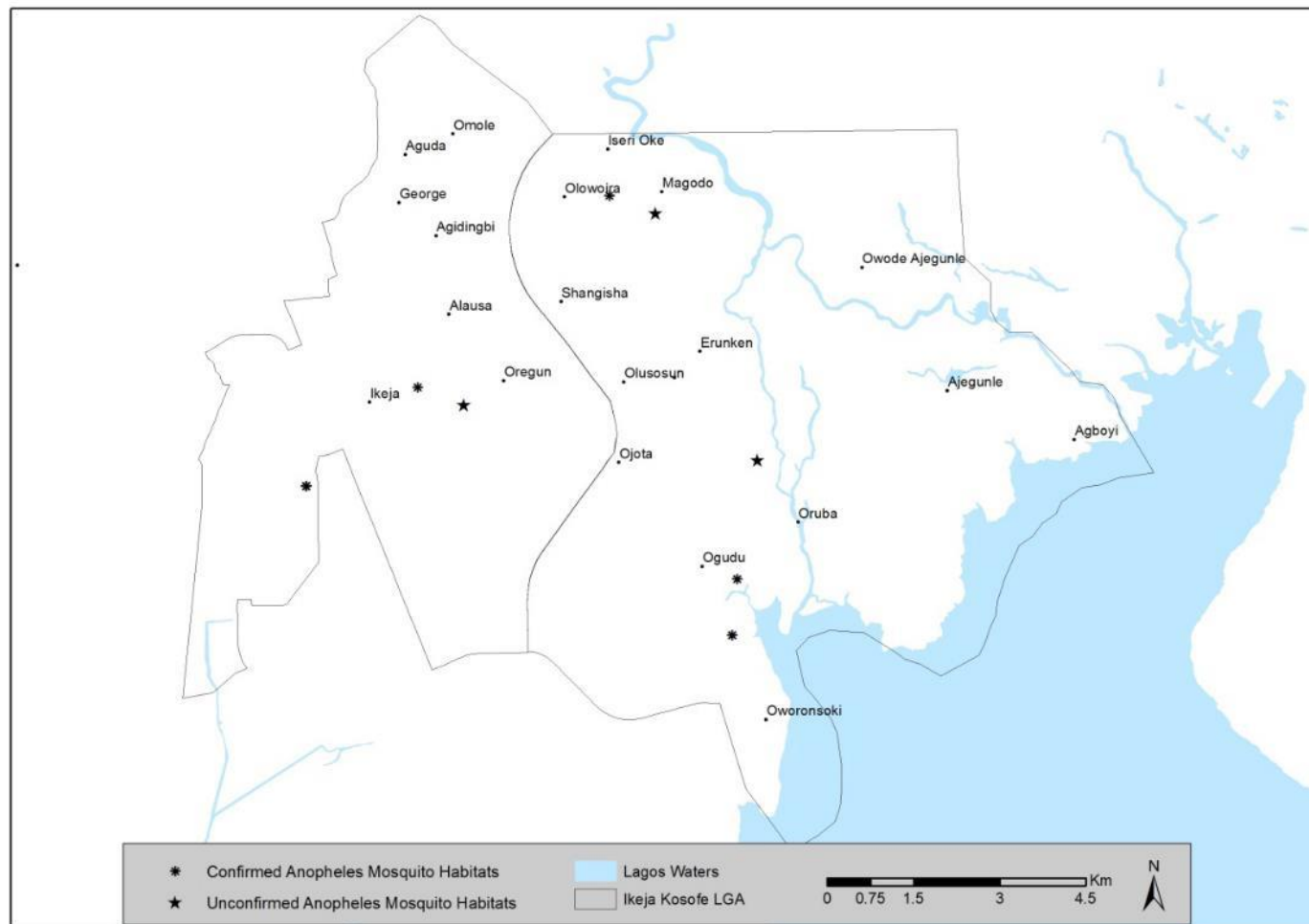


Figure 16: Confirmed and unconfirmed presence of anopheles habitats

4.11 Data Development, Processing and Management

Having collected data on households using the questionnaire survey, direct observation and secondary sources, as mentioned earlier, this section discusses steps undertaken to prepare, process and integrate all datasets prior to analysis. I will use these datasets to prepare a household spatial database that will be analysed for understanding the ecology of urban malaria.

I used SPSS 21 predictive analytics software to compute all measures representing the socio-cultural (behaviour) and built environment, conduct all statistical analysis including predictive modelling (Alemu *et al.*, 2011). I then employed the ESRI ArcGIS 10.1 software and extensions to derive all GIS and remote sensing-based measures of the physical environment, develop spatial databases, and conduct GIS analysis (Sithiprasasna *et al.*, 2005), while I used Expert GPS software to download all GPS waypoints and attributes from the GPS receiver into a GIS shapefile.

4.11.1 Data Verification, Screening and Entry

Even when a study is properly designed and appropriate data collection methods and instruments employed, the data generated can still be plagued with quality issues arising from myriad sources ranging from measurement to non-measurement errors (Blasius and Thiessen, 2012). The purpose of verifying data is to improve its quality by identifying, removing and thus refining any unsuitable data. I conducted data verification, screening and processing as a part of the data management steps. The intention was to derive and develop the household database that would be analysed further.

I assessed the quality of all GIS data sets (water bodies) obtained from secondary sources and updated the records where necessary. I also ensured that the data were in Universal Traverse Mercator (UTM) World Geodetic System (WGS) 84 coordinate system (Ye *et al.*, 2008) for more accurate outputs from analysis. As an initial step I assigned a unique ID to each questionnaire and direct observation protocol in the form of the interviewer initials and number (e.g. AIO1, AIO2, KA3, FO4, FO5 ... etc. (see top right-hand corner of sample questionnaire front page in Appendix XXIII) (Ye *et al.*, 2008).

Considering that the questionnaire survey and direct observation were conducted by four field assistants and the PhD researcher (apart from the five accompanying field assistants), there were concerns with interviewer-related errors. I eliminated all

incomplete questionnaires/direct observation protocols i.e with those with item non response issues (at the end of survey), followed up item non-responses and clarified any ambiguity in responses with the field assistants and participants by telephone. I noted all questionnaires and direct observations which had item non-response issues, but did not eliminate them at this stage. I also noted participant status (heads of household/spouses or adults above 18 years of age) for all questionnaires. I reviewed all responses to questions in the questionnaire survey, collapsed responses and recoded for new variables, for example those assigned under the “other” category or open-ended questions (Ye *et al.*, 2008; Bryman, 2012). I then created and applied a final coding template used to code all the questionnaires. I also coded responses in the direct observation protocol, converting them into a quantitative measure and integrated it alongside the questionnaire survey.

As indicated earlier, this research uses various computer software packages to undertake different aspects of the research and this necessitated the frequent back and forth conversion of datasets to meet software compatibility demands. I entered all responses from the questionnaire, including details such as question ID, interviewer ID, questionnaire number, date of interview, etc., and direct observation data into the SPSS 21 predictive analytic software (Alemu *et al.*, 2011). For ethical reasons, I did not enter any participant identifiers.

All data previously entered into the SPSS software and the GPS coordinates of the households interviewed were exported into the ESRI ArcGIS software. I joined them together using “Interviewer ID” as the common field (as shown in Figure 18) and then converted into a point shapefile GIS format.

Study House

Shape	Locality	QuesID	ID	Date
Point	Ogudu	F0355	FO028	31/07/2010
Point	Ogudu	F0354	FO028	31/07/2010
Point	Ogudu	F0351	FO028	31/07/2010
Point	Ogudu	F0349	FO028	31/07/2010
Point	Onigbongbo	F0325	FO060	30/07/2010
Point	Onigbongbo	F0324	FO059	30/07/2010
Point	Onigbongbo	F0322	FO057	30/07/2010
Point	Onigbongbo	F0320	FO055	30/07/2010
Point	Onigbongbo	F0318	FO053	30/07/2010
Point	Onigbongbo	F0317	FO052	30/07/2010
Point	Onigbongbo	F0315	FO050	30/07/2010
Point	Onigbongbo	F0314	FO049	29/07/2010
Point	Ikeja Industrial Estate	F0285	FO048	29/07/2010
Point	Ikeja Industrial Estate	F0282	FO045	29/07/2010
Point	Ikeja Industrial Estate	F0281	FO044	29/07/2010
Point	Olowo-Ira	F0245	FO041	28/07/2010
Point	Olowo-Ira	F0244	FO040	28/07/2010
Point	Olowo-Ira	F0243	FO039	28/07/2010
Point	Olowo-Ira	F0242	FO038	28/07/2010
Point	Olowo-Ira	F0241	FO037	28/07/2010
Point	Olowo-Ira	F0240	FO036	28/07/2010
Point	Ikosi	F0192	FO035	27/07/2010
Point	Aiyedere	F0190	FO033	27/07/2010
Point	Aiyedere	F0189	FO032	27/07/2010
Point	Aiyedere	F0188	FO031	27/07/2010
Point	Aiyedere	F0187	FO030	27/07/2010
Point	Aiyedere	F0185	FO028	27/07/2010

Fash1_Project

FID	Shape	time	lat	lon	cmt	ID
9	Point	13/09/2010	6.603629	3.386023	25/07/2010	FO028
10	Point	13/09/2010	6.60988	3.387816	25/07/2010	FO028
11	Point	13/09/2010	6.608363	3.386917	25/07/2010	FO028
12	Point	13/09/2010	6.605446	3.381384	25/07/2010	FO028
13	Point	13/09/2010	6.605579	3.37964	26/07/2010	FO017
14	Point	13/09/2010	6.609675	3.378695	26/07/2010	FO018
15	Point	13/09/2010	6.602644	3.378392	26/07/2010	FO019
16	Point	13/09/2010	6.604747	3.375431	26/07/2010	FO020
17	Point	13/09/2010	6.608261	3.376583	26/07/2010	FO021
18	Point	13/09/2010	6.606324	3.383682	26/07/2010	FO022
19	Point	13/09/2010	6.604281	3.382208	26/07/2010	FO023
20	Point	13/09/2010	6.601924	3.383238	26/07/2010	FO024
21	Point	13/09/2010	6.602351	3.387275	26/07/2010	FO025
22	Point	13/09/2010	6.602498	3.381854	26/07/2010	FO026
23	Point	13/09/2010	6.605562	3.390575	27/07/2010	FO027
24	Point	13/09/2010	6.608542	3.39049	27/07/2010	FO028
25	Point	13/09/2010	6.612846	3.390301	27/07/2010	FO029
26	Point	13/09/2010	6.615353	3.389212	27/07/2010	FO030
27	Point	13/09/2010	6.613019	3.389505	27/07/2010	FO031
28	Point	13/09/2010	6.612055	3.38903	27/07/2010	FO032
29	Point	13/09/2010	6.601165	3.379519	27/07/2010	FO033
30	Point	13/09/2010	6.597231	3.380136	27/07/2010	FO034
31	Point	13/09/2010	6.598305	3.384586	27/07/2010	FO035
32	Point	13/09/2010	6.628185	3.37694	28/07/2010	FO036
33	Point	13/09/2010	6.630548	3.3783	28/07/2010	FO037
34	Point	13/09/2010	6.637283	3.376455	28/07/2010	FO038
35	Point	13/09/2010	6.635113	3.383416	28/07/2010	FO039

Figure 17: Joining of GPS locations of surveyed households and SPSS coding output based on a common field.

4.11.2 Interrater/Interviewer Agreement

Though the five interviewers and five support assistants (10 people in total) that participated in the questionnaire survey passed through rigorous training and displayed good understanding and demonstration of tasks required, issues associated with fatigue, lapses in attention, over-familiarity with the questionnaire, the duration of data collection or even participants' characteristics, as raised by Bailar *et al.* (1977) and Bryman (2012), may still have consequences for the degree of agreement, interviewer variability and biases in the survey data. To account for this, I re-interviewed 20% of the participants, examined if variation exists between the interviewers' interpretation of questions and thus the consequences for the types of responses received. I assessed for agreement using the percentage of similar responses obtained with the re-interviewed participants (Gisev *et al.*, 2013). This shows the consistency, or conformity, of measurements made by multiple interviewers. I achieved 76% agreement with the re-interview process. This is presented once more in Chapter Seven, section 7.2.

4.11.3 Internal Reliability and Validity of Questionnaire and Direct Observation

My research uses scores derived from multiple questions in the questionnaire to arrive at an indicator value for some of the environmental and behavioural variables in Table 3. Cronbach's alpha is used to assess if these multiple questions relate to one another, thereby measuring the coherence and internal reliability of the composite indicator (Foa *et al.*, 1993; Bryman, 2012). Cronbach's alpha varies between 1 (perfect internal reliability) and 0 (no internal reliability) (Bryman, 2012); I utilised the SPSS 21

software to derive values. I assessed the validity of the indicator devised to gauge if the construct really measured the variable. I assessed validity based on findings in the literature, as well as adopting an intuitive process of face validity (Bryman, 2012). Internal reliability values for the indicators range from 0.60 to 0.80, indicating above-average to near-perfect reliability (Bryman, 2012) and is presented for each indicator derived in the subsequent sections and in Chapter Seven.

4.11.4 Derivation and Construction of Variables

This section summarises the methodological approaches in the derivation of measures for the environmental and behavioural risk variables, as presented in Table 3, which contextualise the geographic locations of households interviewed,

The household is the unit of study in this research, as in similar studies (Ngom and Siegmund, 2010), for which I gathered data on 505 households. It is defined as people living together in the same residential unit, sharing consumption, economic and child-bearing responsibilities where applicable (Afrane *et al.*, 2004). For the Nigerian cultural setting, this includes the extended family, the polygamous family, relatives or domestic servants participating in any of the above within the same residential unit for which the head is normally the man and in their absence woman.

Examining the complex relationship between these variables requires objective measures that accurately represent real-life risks and exposures. However, the development of this measure is a complex process and may be a source of inaccuracy and variations in results deriving from studies. The findings showed that there is no one “gold-standard” representation of urban malaria, its environmental and behavioural risks, but rather that this depends largely on the study type, data availability and focus of the research. Thus, I identify and represent indicators and measures of the environmental and behavioural variables in Table 3, based on findings in the literature, or develop new ones where necessary. Though many measures from the literature were derived from single variables, my research will derive some measures from a composite of variables that have been logically grouped to belong to the same sub-themes. In doing so, the goals are to reduce the complexity of the multivariate model integrating these variables and create new measures that thematically express a better significance to malaria than initial variables taken individually (Ngom and Siegmund, 2010).

As these measures are sourced from the questionnaire, direct observation protocol, GIS and remote sensing imagery data and analysis, it thus applies conventional geographic

research instruments to an emerging type of disease, making it an imperatively exploratory work and thus has its strengths and weaknesses.

4.11.4.1 Malaria in the Household

This is defined as the occurrence of malaria in any member of the household irrespective of frequency of occurrence (Keating *et al.*, 2005; Ngom and Siegmund, 2010). It measures the presence or absence of self-reported malaria or febrile illness in the household in the last 12 months (Fernandez Castilla and Sawyer, 1993; Ngom and Siegmund, 2010), using the questionnaire in Appendix XVIII, and represents the dependent variable. This is measured as a burden on that household. While similar measure has been used by Keating *et al.* (2005) and Deressa *et al.* (2007), it is weakened for a number of reasons. Firstly, recall bias; secondly, inability of participants to decipher malaria from other illnesses with similar symptoms; thirdly, representing multiple occurrences of malaria in a household as a single occurrence at household level can present a diminished or enfeebled account of the disease's intensity in a population. However because the unit of analysis is the household, multiple occurrences of the disease in a single house still marks that household haven been previously infected. Similar approach has been used by Ngom and Siegmund (2010) in representing malaria at household level. I have selected household as the unit of analysis in order to account for the burden which households encounter when any member of the household irrespective of age experiences the disease. When malaria or its consequences such as death occurs in any household member, the household as a whole feels the loss making it a burden for not just the individual but the household. The burden of malaria in the household is based on the premise that any infection from malaria irrespective of frequency has not only economic impact on the household, but also emotional, social or otherwise and thus making the unit of household a viable unit of study (Keating *et al.*, 2005; Ngom and Siegmund, 2010). This is a binary response variable.

4.11.4.2 Indicators of Behaviour – Socio-cultural Environment

In this study, 11 independent risk variables (IRVs) associated with behaviour/socio-cultural environment listed in Table 3 have been derived from a combination of many single and multi-dimensional responses to questions coded from the questionnaire (Appendix XVIII) as applied by Ngom and Siegmund (2010). These data is derived at the household level irrespective of the household member it applies to bearing in mind that it is the unit of study and I focus on household burden and not individual experiences.

These variables are ethnicity, religion, educational qualification of head of household (Keating *et al.*, 2005) defined according to the Nigerian educational system, and occupational rank of head of household as adapted from the International Labour Organisation and the Nigerian Occupational Code (International Labour Office, 2007; Nigerian Labour Organisation, 2009). I removed questions on pregnancy and non-immune travellers due to poor response rate. Rather, I derived data on households with vulnerable members using only the presence of any child below the age of five years. I derived travel history data based on travel patterns to the outskirts of and outside Lagos state in the last year.

Wealth index as a proxy of income is measured by applying principal component analysis (PCA) to ownership of 22 assets as applied by Filmer and Pritchett (2001) in a developing country context, where income and expenditure data is unreliable and difficult to gather. The resulting index is further classified into five, using cut-off percentiles of very low (30%), low (25%), average (30%), high (10%) and very high (5%) (Vyas and Lilani, 2006).

“Level of knowledge” represents the amount of knowledge displayed at a household level based on the composite of responses given to a set of weighted questions described in the following expressions: where knowledge of cause of malaria (K_{cm}) is “Yes”, then = 1; where knowledge of malaria symptoms (K_{ms}) is at least three, then = 0.5; where knowledge of malaria symptoms (K_{ms}) is less than 3 then = 0; then, Level of Malaria Knowledge (L_{mk}) = $K_{cm} + K_{ms}$.

Level of knowledge is summed from the two questions about malaria, with cause of malaria having a higher weight. The resulting index is scaled and ranked as follows: 0 represents no knowledge; 0.5 represents poor knowledge; 1 is for good knowledge and 1.5 is for a very good level of knowledge about malaria. The internal reliability is very high, with a Cronbach’s alpha of 0.80 (Bryman, 2012).

“Working at night without mosquito protection” is derived as follows: if at least one household member does a night-shift job, either inside a building without protection, or outside, with or without protection = 1; and if all household members do not do a night-shift job or a household member does a night-shift job but works inside the building with protection = 0. The weakness of this indicator is that it quantifies neither night social activities nor the geographic locations of workplaces, unlike other vector-based

pathogenic disease studies where an activity space model is applied (Stoddard *et al.*, 2009).

A household is said to have a belief if the response to any of the statements derived from the questionnaire is “yes”: belief in the transfer of malaria through human contact; belief in any of the following as a cause of malaria: sun, heat or fire; eating of oily and fatty foods; eating over-ripe/under-ripe mango; constipation; alcohol; houseflies; and belief in malaria being transmitted through breastfeeding.

Preventative behaviours describe actions that protect members of a household from the infectious bite of mosquitoes. In this research they are represented as Human Avoidance Actions (H_{ac}) and actions that destroy the vector mosquitoes, known as Vector Destruction Actions (V_{da}). I employ Ngom and Siegmund (2010) approach by deriving the variable from a multiple of key weighted variables from the questionnaire survey in Appendix XVIII.

A	Door net
B	Window net
C	Mosquito coil
D	Repellent gel
E	Insecticide spraying or any form of vector control (VC_u)
F	Insecticide-treated mosquito net usage (ITN_u)

$$H_{ac} = \frac{A + B + C + D}{N}$$

Where A, B, C, D, E, and F are defined as above

H_{ac} is the Human Avoidance Action, N = no. of variables describing H_{ac}

$V_{da} = E + F$ Where $E = VC_u$ and $F = ITN_u$

$P_{bh} = H_{ac} + V_{da}$

P_{bh} = Preventative behaviour

4.11.4.3 Measures of Physical and Built Environmental Variables

Here, I measure the 15 environmental variables as listed in Table 3 using responses from the questionnaires, direct observation protocol and those derived from GIS and remote sensing sources.

Measures representing housing quality that have been employed in the literature include but are not limited to: house type, design, roof, wall and window materials and presence of window and door screens. Often their selection has been applied to suit the local context. Housing quality is represented here by the condition (holes) of walls (Peterson *et al.*, 2009), doors and window nets which are derived from the direct observation of housing materials in the sample of households. Homestead risks, such as the presence of any vegetation that include bushes, grasses, gardens and farmyards, and the presence of any stagnant water within 200m from the household location, were directly observed and noted using the direct observation protocol.

“Proximity to anopheles vector mosquito habitat” measures the distance of the household residence from anopheles breeding locations. This measure, presented in Figure 19, is derived by applying the spatial analyst Euclidean distance tool in the ESRI ArcGIS 10.1 software to the entomological spatial dataset discussed earlier (Machault *et al.*, 2010). The final value is extracted from each geographic location of the 505 households as attributes from the figure using the Spatial Analyst Extract Multi-values extension in ESRI ArcGIS 10.1 (Sithiprasasna *et al.*, 2005).

Apart from entomological data representing sites of vector presence, I also measure vector presence using habitat types, such as water bodies, reported in the literature to also harbour anopheles. These water bodies include creeks, swamps and mangroves and exist as secondary-sourced GIS data. Figure 20 shows the results of applying Euclidean distance with results assigned to households, as similarly utilised earlier in the entomological data.

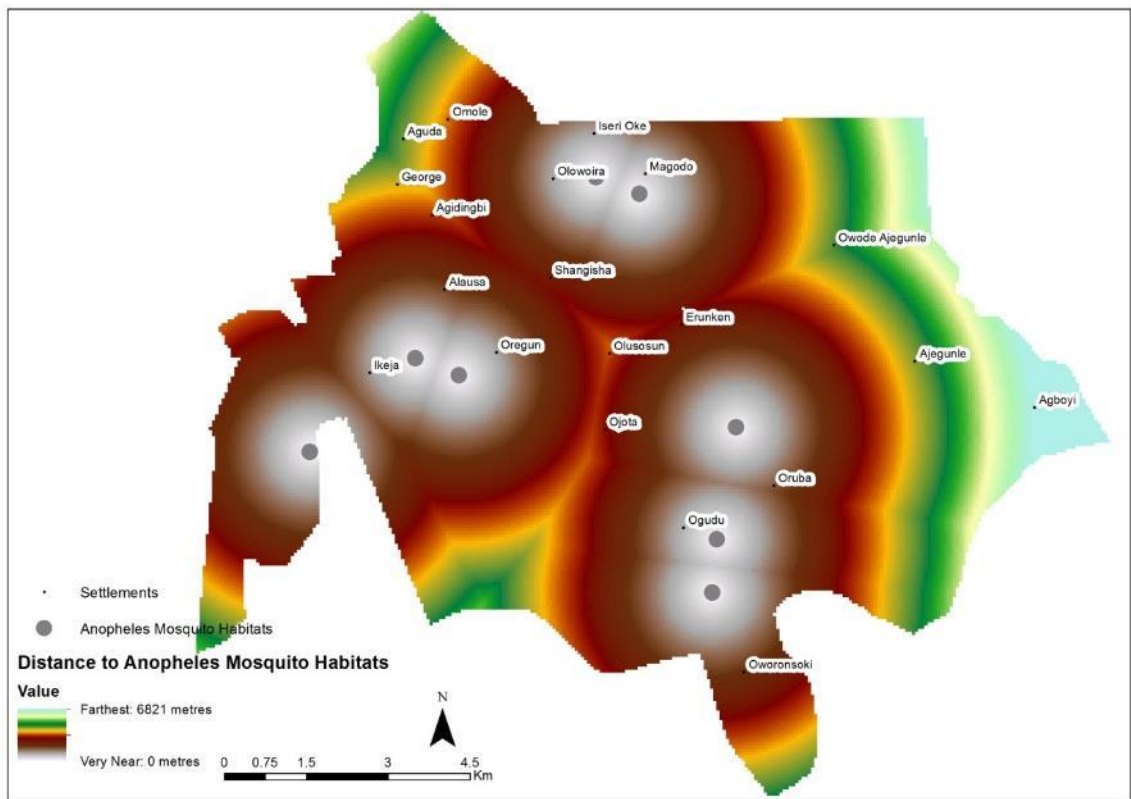


Figure 18: Proximity to vector breeding habitats

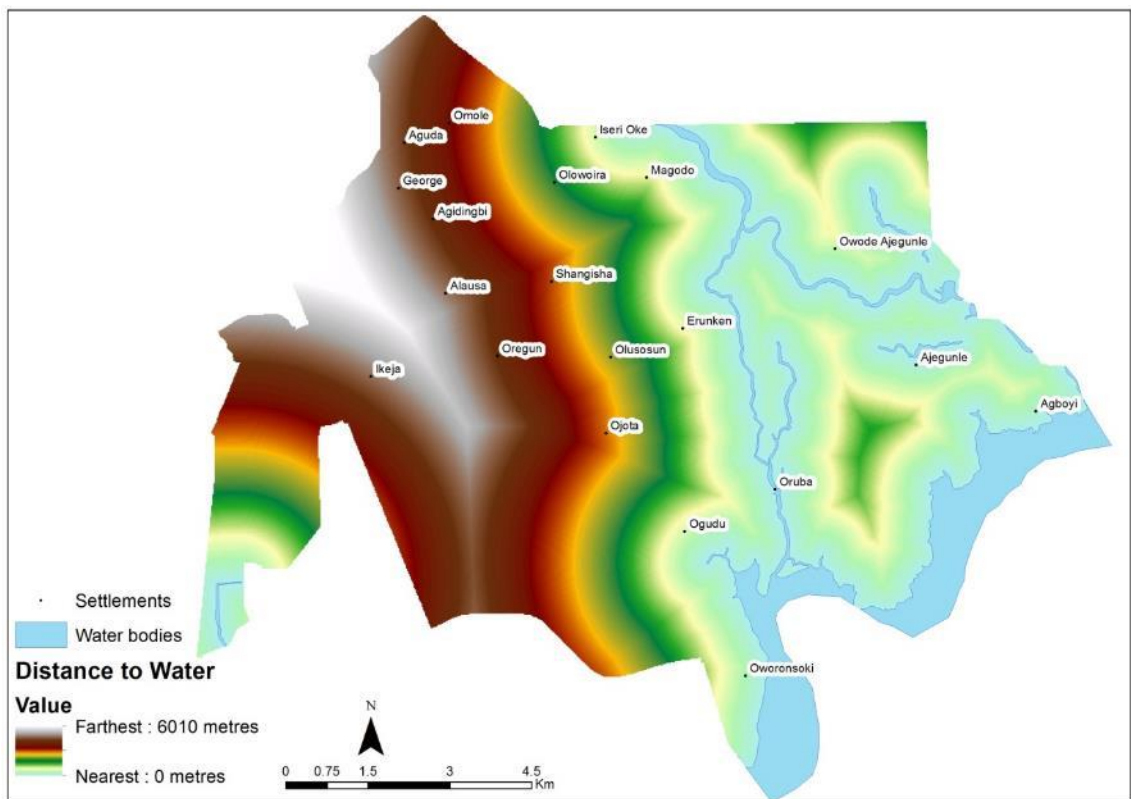


Figure 19: Proximity to water bodies

Farms have been reported as vector breeding habitats, and animals as alternative feeding sources for the anopheles; and they have been influential in urban malaria risks (Afrane *et al.*, 2004). In this research, I gathered the coordinates for farms and animal husbandry locations in the study area, using the Etrex Garmin GPS receiver. I downloaded it with the Expert GPS software into the ESRI ArcGIS 10.1 software, where I derived the distance, as shown in Figure 21, and assigned this measure to the 505 households, as carried out earlier with the anopheles breeding habitats.

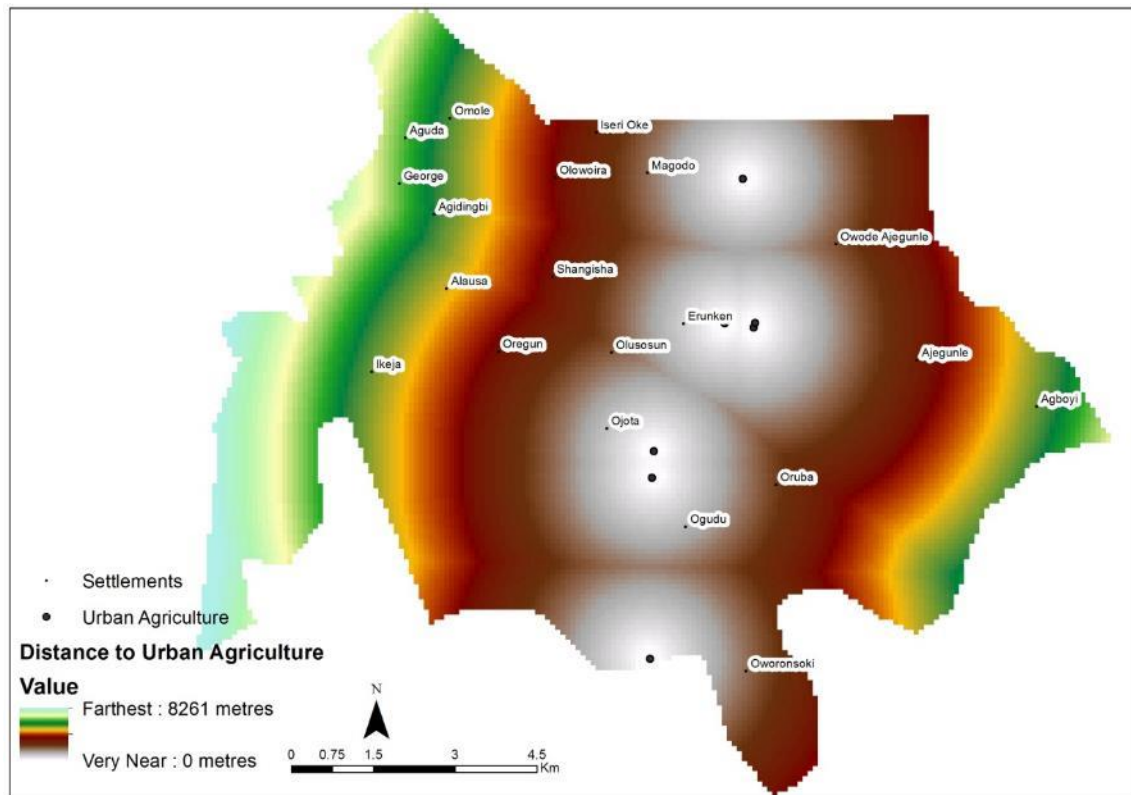


Figure 20: Proximity to urban agriculture sites

Topography in this research is used to describe landscape features such as elevation and slope, known to be influential in the risk of malaria, even in low-lying areas. Here, I measure elevation using the Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) data with a spatial resolution of $90\text{m} \times 90\text{m}$ downloaded from the CGIAR Consortium for Spatial Information (CGIAR-CSI) website (CGIAR - Consortium for Spatial Information (CGIAR-CSI), 2004) over the Advanced Space-borne Thermal Emission Reflection Radiometer Global DEM (ASTER GDEM) with a spatial resolution of $30\text{m} \times 30\text{m}$, demonstrated by Clennon *et al.* (2010) and Nmor *et al.* (2013) to have poorer accuracy in representing landscape indices associated with vector breeding. A topographic map, as another alternative (Cohen *et al.*, 2010), was not

available for this study. Slope is derived from the SRTM DEM using the 3D analyst extension of ESRI ArcGIS 10.1. Elevation and slope are presented as Figures 22 and 23 respectively.

The purpose of these measures is to characterise a 200m buffer around of the geographic location of the households to accommodate the modelled foraging range of the anopheles mosquitoes (Gu and Novak, 2009), as also similarly carried out by Cohen *et al.* (2010) and Dambach *et al.* (2012). I derived summary statistics (mean value) within and around the 200m buffer by applying the Hawth Zonal statistics ++ tool (Schmiding *et al.*, 2009).

The DEM used for this study is limited in its spatial resolution of $90\text{m} \times 90\text{m}$ as stated earlier. This means that the topographic characteristics of any feature that is smaller than $90\text{m} \times 90\text{m}$ in size will be summarised to the pixel value. However, as stated earlier, in the absence of a topographic map, which would require more resources to derive topographic information, it is of better accuracy than the ASTER GDEM (Clennon *et al.*, 2010; Nmor *et al.*, 2013). While the limitation of this dataset has been acknowledged, consequences for analysis is such that the actual topographic value (elevation and slope) that occurs on the ground within this particular spatial resolution of $90\text{m} \times 90\text{m}$ would be oversimplified by using a single summary value to represent every 90m by 90m . However, oversimplification is minimal because Lagos is an almost flat terrain with minimal changes in elevation as noted with the elevation range in the study area which is between -11m and 54m.

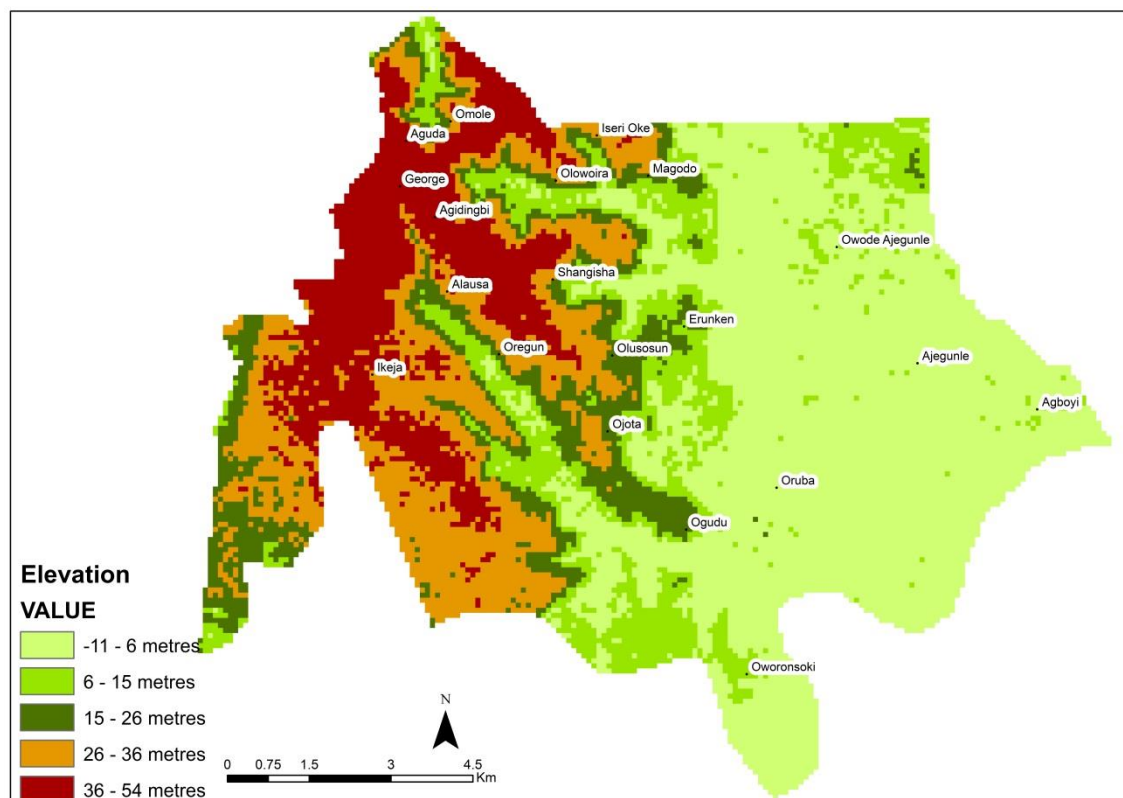


Figure 21: Elevation for Ikeja and Kosofe LGAs, Lagos

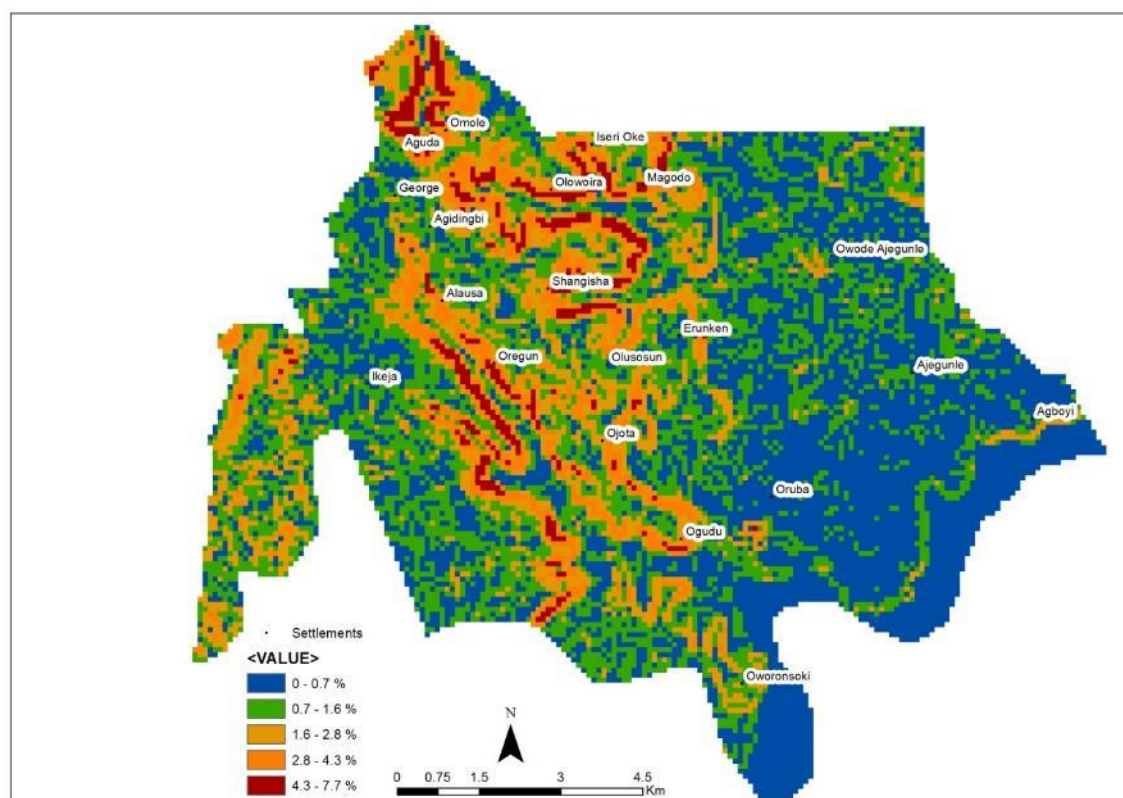


Figure 22: Slope characteristics for Ikeja and Kosofe LGAs, Lagos

Microclimate characteristics have a huge influence on the regionalisation of malaria, particularly as they impact on vector distribution and population dynamics and in turn the spread of the disease. While it may be an important variable, it is worth noting here that measuring climate at small geographic scales, such as my study area, can be a challenge due to inadequate distribution of meteorological stations to spatially characterise individual households. Under these circumstances, I employ NDVI (Normalised Difference Vegetative Index) as a surrogate measure of climate, as well as characterise vegetation and land use. It is derived from remote sensing imagery and is based upon the inverse relationship between vegetation and land-cover brightness in the red and infrared bands of the electromagnetic spectrum (Hay *et al.*, 1998a; Rogers *et al.*, 2002; Machault *et al.*, 2010).

In this study, NDVI is derived from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) remote sensing imagery of January 2003, acquired from the United States Geological Survey (USGS) website (details in Table 5) (M. C. Thomson *et al.*, 1997; Hay *et al.*, 1998a) using the Image Analysis extension of the ESRI ArcGIS 10.1 software and applying Equation 1. The resulting NDVI output, presented as Figure 24, falls between -1 and +1 and indirectly measures climate through the different vegetation and land-cover types. The NDVI classification followed the guide developed by the United States Geological Survey (USGS, 2011) but was further groundtruthed locally to arrive at a final classification of:

- -1 to 0: Water
- 0.0 to 0.2: soil with built-up area
- 0.2 to 0.3: mixed vegetation with built-up area
- 0.30 to 1: more dense vegetation cover

Table 5: Landsat ETM+ Imagery Characteristics

<i>Date of Acquisition</i>	<i>Path/Row</i>	<i>Temporal Resolution</i>	<i>Spectral Resolution</i>	<i>Spatial Resolution</i>	<i>Radiometric Resolution</i>	<i>Cloud Cover</i>	<i>Processing Level</i>
23/01/2003	191/55	16 days	8 bands	30m	2 ⁸ (256)	0.75%	ETM+ L1T

Source: USGS Earth Explorer Website (2010)

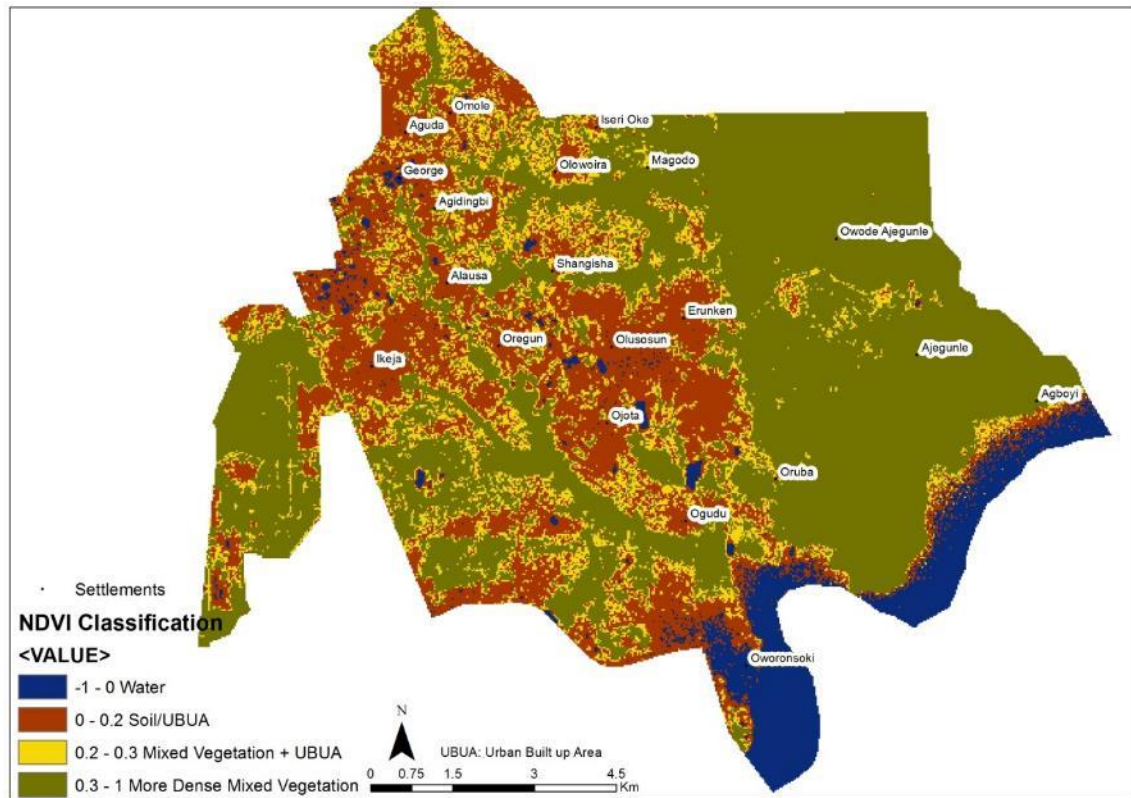


Figure 23: NDVI classification of Ikeja and Kosofe LGAs

The NDVI value is used to characterise household location, as applied similarly to derive topographic characteristics.

While NDVI typifies land-cover and vegetation characteristics, it is important, as it captures some combined effects of temperature, relative humidity, rainfall, sunlight, altitude, land use and land cover in one value (Machault *et al.*, 2010). However, this measure is also limited in several ways: the date of imagery is as far back as January 2003 and the measure is sensitive to atmospheric degradation. I have used the Landsat ETM+ 2003 imagery because of its cost constraints and availability for the study. The ETM+ instrument failed on 31st May 2003, which caused permanent gaps and holes in all imageries acquired after May 2003. Even with gap-filling algorithms which still depend on older imageries, these imageries are still characterised by holes, leaving the pre-May 2003 imageries as the most suitable for this research. Other imageries considered, such as Spot and QuickBird, are commercial imageries though with better spatial resolutions (5m × 5m and 1m × 1m respectively) was beyond the resources of this study. The QuickBird imagery donated for this research by the Geography Department, University of Lagos was not suitable because it did not have an infrared band. Other free downloadable imageries, like the Advanced Very High Resolution

Radiometer National Oceanic and Atmospheric Administration (AVHRR-NOAA) weather imagery, have a poor spatial resolution of $1.1\text{km} \times 1.1\text{km}$; using this has consequences for oversimplification and loss of information on features smaller than $1.1\text{km} \times 1.1\text{km}$ in size. This limitation of using the Landsat ETM+ 2003 imagery data was minimised by updating and groundtruthing the output during fieldwork.

The sensitivity of the NDVI to atmospheric degradation is minimised by using it qualitatively as a mapping device and through the classification of NDVI values, as shown in Figure 24. The final values are assigned to the households, as carried out earlier for other variables.

The results of these processes were written as attributes into the spatial database of the households surveyed, which is already populated with behavioural risk variables.

4.11.5 Database Development and Analysis

At the end of the main study, a spatial database of 505 households in the UTM WGS 84 coordinate system, characterised by 26 behavioural, built and physical environmental risk variables, was developed. As noted earlier, they were collected, derived and measured with a questionnaire survey, direct observation, GIS data and remote sensing imageries. These risk variables quantify place processes for urban malaria in households. The relationship between the 26 variables and urban malaria in households are examined using a number of quantitative methods during the development and assessment of a predictive model of statistical and public health significance. The end purpose is to study and understand the ecology of urban malaria in Lagos state. Only complete household cases were finally used for analysis (Chapter 7).

4.11.5.1 Assessing Urban Malaria Transmission Risks in Households

As an initial step to examining the relationship between environmental variables and the risk of urban malaria in the Ikeja and Kosofe LGAs, I performed a frequency analysis, and correlation analysis on the household spatial database. This is to reveal the underlying characteristics of the households prior to in-depth analysis of the dataset. For further investigation, I employed univariate and multivariate analysis to examine how single and multiple variables operating within the human ecological framework influence place processes and become risk variables for malaria in households (Klinkenberg *et al.*, 2005; Nahum *et al.*, 2010).

Due to the binary nature of my dependent variable as the presence or absence of malaria in the last year in households, this makes it a dichotomous data type. Though the discriminant analysis method was considered, the most suitable statistical analysis method that assesses a range of data types with a binary response data as featuring in this research is the logistic regression method (Hosmer and Lemeshow, 2000; Tabachnick and Fidell, 2012).

Logistic regression was applied as a statistical and model development tool. The strategy is to draw on a single variable or combination of variables from the vertices of the ecological framework, as adopted in this research, to develop ten theoretically relevant models of urban malaria risks that are of statistical and public health significance without employing a step-wise method (Tabachnick and Fidell, 2012). This multivariate framework is an important construct to understand malaria risks owing to the multiplicity of influences to risks in households as well as those affecting the vector and parasite dynamics/sustenance.

As a first step, I developed the initial two predictive models from variables drawn from the human ecology of disease theoretical framework in a univariate logistic regression, with $p \leq 0.05$ and $p \leq 0.25$ (Klinkenberg *et al.*, 2005; Nahum *et al.*, 2010). The variables in the subsequent eight models are associated with the vertices of the disease framework and one statistically significant interaction term.

To assess the capability of the ten predictive models, I employed the goodness-of-fit statistics and predictive capability. After the development of candidate predictive models, the AIC approach was used to evaluate and select the relatively best model. I progressed to select the most parsimonious model from the ten predictive models using, in particular, the improved Akaike Information Criteria (AICc) (Bozdogan, 1987). The AICc shows a penalised measure of fit based on the number of parameters and a measure of relative goodness-of-fit from a set of candidate models, and takes the sample size into additional consideration. In this improved AICc, there is a greater penalty for a large number of IRVs. The AICc considers each model's log likelihood, sample size and number of environmental and behavioural risk variables. The weakness is that it does not show how well a model fits the data but rather selects the preferred model with the minimum AICc value, but penalises for too many independent environmental risk variables and over-fitting.

I assessed the contributory influences of environmental and socio-cultural risks of malaria using the odds ratio and its p-value (Hosmer and Lemeshow, 2000; Bewick *et al.*, 2005). I utilised GIS selection queries to select multiple environmental risk variables from the candidate models for further exploration. Overlay analysis was applied to visualise the patterns of multiple environmental risk variables (Cromley and McLafferty, 2012).

To engage with the current scholarship in the sub-discipline of medical and health geography, I utilised findings and quotations from the semi-structured interviews conducted in the pilot study as contextual backdrops to explain the statistical and public health significance of relationships (Creswell, 2009). The narrations emanating from the interviews represent human expressions of place processes (Kearns, 1993; Kearns and Moon, 2002; Cutchin, 2007).

4.12 Feedback from Main Study

This section discusses feedback lessons from the main study and some of the difficulties faced during fieldwork that impacted the research.

4.12.1 Reasons for Use of Field Assistants

It is common practice to use field assistants when their presence will make a difference in reducing fatigue, if there are cultural constraints and where time is a limitation. Their help has been enlisted to improve efficiency in similar studies (Alemu *et al.*, 2011). In particular, similar urban malaria studies have been conducted across two seasons: dry (pilot study: March to May 2008) and rainy (main study: June to October 2010) (Baragatti *et al.*, 2009; Machault *et al.*, 2010) when vectors vary in abundance and disease transmission may vary accordingly, as noted in Lagos state (Awolola *et al.*, 2002b; Okwa *et al.*, 2007); I wanted to apply similar seasons in this study, meaning that time was a restriction; in addition, there was anticipation of flooding from the Ogun-Osun river basin which often flooded parts of my study area. There was also political insecurity resulting from the Lagos state government infrastructural development initiative, which led to residents losing their property (see Appendix XXII). As such, my timing was restricted to these periods and I thus needed field assistants to achieve 505 interviews that were 30 to 45 minutes long.

As noted earlier in the feedback from the pilot study, preparatory stages of main study, recruitment and training of field assistants sections of this chapter, the ten team members recruited, working in pairs with only five interviewers (inclusive of the PhD

researcher) carrying out the questioning, were indispensable in the progress of the fieldwork. Despite their advantages, there were still concerns with interviewer-related errors, one of which was the lack of response. To avert this, Fowler (2009) suggests taking precautions such as giving proper training, supervision, feedback, and reviewing the completed questionnaire, which as noted earlier were implemented in this study.

Despite having a large pool of interviewers, the workload per field assistant was still higher than Snow *et al.* (2008) and Kearns and Joseph (1993) which was likely to increase interviewer error, but this influence was minimised through re-interviewing 20% of the sample. Apart from this, during the fieldwork, we experienced a number of setbacks that had consequences for incomplete questionnaires, direct observation, non-response issues, and the health and safety of the interviewers.

4.12.2 Reduction in Sample Size and Lack of Responses

The aim of the pilot study was to identify issues that would affect the main household study, which included the questionnaire survey and direct observation (van Teijlingen and Hundley, 2001). However, Treece and Treece (1986) and Lackey *et al.* (1998) state that, even with a pilot study, not all flaws of a main study show up, due to the small sample size, the artificial situation, limited scope, and above all, the context.

I anticipated non-responses and difficulties in accessing heads of household and navigating the whole process of interviewing; these relate to some of Peil *et al.* (1982) experiences of fieldwork in Nigeria. However, what I did not anticipate is the way the political situation³⁶ (see Appendix XXII) would affect the study, particularly the direct observation aspects, that questions in the questionnaire might still go wrong even after reworking them with the experiences in the pilot study, pre-testing and not having the chance to follow up incomplete surveys. In other words, while I accommodated item non-responses in the contingency factor applied to the final sample size to arrive at a total of 505, and in the event of non-response for the final sample size of completed surveys to fall between 109 and 316, which I still achieved, the chance to follow up and improve on non-responses, incomplete questionnaires and the sample size proved difficult, owing to health and safety issues experienced during the main study fieldwork.

The major loss in responses emanates from the direct observation aspects of the survey. While the participants were more willing in answering questions from the questionnaire

³⁶ Lagos state government had a regeneration project to build roads, gardens etc., which meant that people's personal lands had been acquired under difficult circumstances.

that did not relate to their houses, they were less so when we wanted to observe their housing environment. At that point many interviews ended, leading to incomplete household data. There were non-response issues with other economic-related and housing elements of the questionnaire that also led to sample size reduction; I also eliminated non-heads of household questionnaires, participants who withdrew and other non-response variables. More details are given in Chapter Seven.

4.12.3 Follow-up of Non-responses and Issues of Health and Safety

As described earlier, some of the reasons for sample size reduction are incomplete household surveys from the direct observation of housing qualities and environments parts of the questionnaire; and elimination of questionnaires related to non-heads/spouses of household. Part of this occurred in my pilot study and one of the feedback items implemented was to ensure I obtained appropriate contact information to follow up participants should such circumstances occur. I trained the field assistants, as described earlier, to gather appropriate contact information in case the participants needed to be contacted.

I addressed concerns with health and safety (H&S) that could be followed up during data collection, and changed questioning strategies where necessary, provided more identification where needed and followed up on respondents when H&S permitted. I gave interviewers the flexibility to reorder questions to suit the interview situation. I re-interviewed 20% of the questionnaires to minimise inconsistencies (Ernst *et al.* 2009). These changes in strategies, even though they achieved improved response rates for questionnaires, were less successful with direct observation. They still did not eliminate the way the respondents viewed us under the then political climate. We were often mistaken for government officials and even threatened in some communities, despite showing appropriate identification, ensuring and demonstrating they had a good understanding of the study objectives and assuring them of confidentiality. This affected access to certain locations and incomplete household surveys, especially for questions they considered sensitive/personal in the “eyes” of the public (housing, assets, environment and health) or might put them at risk for government enforcement initiatives.

Despite these, I followed up incomplete questionnaires immediately by changing data collection strategies and following up by telephone where contact numbers were made available (see Appendix XXIII for efforts in this respect). Some respondents responded

by telephone, others appreciated a face-to-face follow-up, while others refused and even withdrew from the process. The main reason given for non-response was the political context. It was unsafe to follow up by visiting some of the respondents due to the previous aggression and the political context as well as the flooding from the Osun-Ogun river basin of downstream communities of Kosofe LGA in October 2010 (see Appendix XXIV). The study was affected because the transportation infrastructure was cut and some respondents were displaced. Following them up in that instance for incomplete surveys was unrealisable and for ethical reasons, I did not go beyond these attempts. It was these uncertainties that I took into consideration when estimating a contingency factor for item non-response in my sample size calculation as applied by Nahum *et al.* (2010) under similar circumstances.

Due to the nature of this study, which required data on households' residential locations, invading their privacy and the use of hospital data, it was necessary to consider the ethical implications.

4.13 Ethical Considerations

The research was made up of two phases, a pilot study and a main study, both of which required interviewing human participants at their place of residence and use of secondary data sources, some of which were aggregates of malaria cases reported from health care facilities. As a part of the research process, I ensured consideration of ethics, sought ethical clearance, and reviewed it in accordance with ethical principles guiding health and social research involving human respondents, as set out by the World Medical Association's (WMA) Helsinki ethical principles (World Medical Association, 2008), Newcastle University Ethics Committee, Federal Ministry of Health, Abuja, Nigeria, and studies that have been conducted under similar conditions.

My research mainly covered three broad data collection and analysis areas:

- Aggregate malaria infection data from health care facilities;
- Household surveys including interviews and direct observations;
- Environmental investigations.

I undertook a health and safety risk assessment as a prerequisite to ethical clearance from Newcastle University. During the course of my research, I took into consideration the following: respect for the rights of my respondents and their fair treatment; the need

to promote the interest and wellbeing of my respondents (beneficence) and not to do harm (non-maleficence); the wider direct and indirect impact of my research in its local context (Peil *et al.*, 1982; Kobayashi, 2001). I achieved these by implementing informed consent, confidentiality and privacy as well as respect for the rights of participants, assessing their vulnerability and providing a feedback mechanism for participation, tailoring it to the local context where needed (Peil *et al.*, 1982; Kobayashi, 2001; Valentine, 2001). These efforts are discussed.

4.13.1 Respect for Rights of Respondents

As part of putting ethics into practice, my semi-structured interviews, questionnaire surveys and direct observations targeted only mentally competent adult heads of household/spouses or household members above 18 years. I did not interview those who lacked competence to respond freely to the interviews. I also employed an opt-in approach to seek the participation of these participants (Valentine, 2001).

4.13.1.1 Informed Consent

Prior to the household surveys, I visited and briefed community leaders and traditional chiefs of my research, and where applicable sought initial permission to undertake my study in their communities. During the household surveys, I provided verbal details and written information sheets on the research to participants as presented in Appendices VI, VIII and XVIII for the semi-structured interview, pilot questionnaire survey and the main study respectively. I also clarified any concerns they had and obtained informed consent before proceeding with the interview.

The purpose of the verbal details and information sheets were to make full disclosure and ensure the respondents had a full comprehension and understanding of the project and what they were committing themselves to. The sheet contained information on the project, fieldwork objectives, institution affiliation, researcher and supervisor contacts, funders, degree expected, incentives for participating, risks, benefits, and what participation entailed. As part of the briefing, the respondents were informed that their participation was voluntary, they could refrain from answering any question and they could withdraw at any time from the research at their request, even though the interviewing process had been completed and incentives received. The field assistants who participated in the study were trained to do the same. They were also provided contact details for any arising concerns. This information was explained in English, the

local Pidgin English and/or Yoruba where applicable. During the course of the main study I permitted 12 participants to withdraw their consent and leave the study.

4.13.1.2 Privacy and Confidentiality

The risk of confidentiality, intrusion of privacy and anonymity of respondents' personal information did not arise while I was collecting malaria infection data from hospitals because the data provided is aggregated on a monthly basis and no identifiers are revealed. I also did not need to access patients' records. All data was abstracted from registers having only the aggregate number of disease counts and not linked to any personal identifier.

There were confidentiality issues I considered during the household questionnaire and interviews at the pilot study and main study phase. As part of the information sheet and briefing of respondents, I assured them that their information would be kept confidential and identities would be anonymised. I managed the protection of respondents' identities by using anonymous questionnaires and interviews. All completed hard-copy questionnaires and interviews were kept in my custody under lock and key. All digital forms of the interviews and questionnaire data in computer storage required passwords. I removed all identifiers and used anonymised IDs to attach attributes to the respondents such that they could not be identified.

As part of maintaining the privacy and confidentiality of respondents, during the mapping of the household survey data, I displaced participants' geographic location up to about 150m as suggested by Dragioevio *et al.* (2004); and as employed in the DHS (Nigerian National Population Commission (NPC) and ICF Macro, 2009). This aspect was important to some participants, especially in the political context within which we were gathering household data. It was very important I ensured and assured the participants that they would not be identifiable by their personal attributes or their geographic locations. All identifiers pertaining to these were addressed.

Due to lack of informed consent by some participants to disclose, disseminate and publish direct quotations of from interview, according to limitations imposed by the UK Data Protection Act for any research produced within the UK (Valentine, 2001), I have eliminated their names and all identifiers in the publication of my research thesis. I have only used direct quotes from participants who gave additional consent to use it.

With respect to malaria infection data and its quality assessment, I obtained prior permission with the LSMoH before embarking on data collection. I adopted a participant approach in observing, conversing, and interviewing members of staff on quality issues associated with the data and the reporting system. The institution and staff were aware of my research objectives and gave permission for the data-gathering. The names of staff interviewed are not revealed. I have also shared the findings with them prior to documenting them as part of my thesis and they are content with them.

I have worked with the list of enumeration areas (EAs) of my study area provided by the National Population Commission (NPC). NPC has restricted the publication of the list of EAs to only one page. This has been respected.

4.13.2 To Promote the Interest and Wellbeing of the Respondents

I conducted the semi-structured interviews by myself and the questionnaire survey with field assistants, who were postgraduate students, university graduates, final-year university students and qualified teachers. We were all knowledgeable about local customs and local languages.

As the place of survey was the residence of the respondents, I anticipated that intrusion into private property and communities at untimely hours would occur. We were tolerant and respectful towards this, we avoided night visits to minimise intrusion into personal space, local customs and traditions, and visited homes only between 8am and 6pm. We avoided entering participants' homes for our own security, as this was part of the risk assessment conditions to receive ethical clearance from Newcastle University, as well as working late hours to meet participant availability even though it affected our flexibility. This was also for the comfort of the participants. However, on most occasions there was minimal need to enter their accommodation because it was quite easy to meet the participants outdoors (apart from the high-income groups) as they live a very outdoor lifestyle. It is easy to find them sitting leisurely in front of their homes and interacting with their neighbours.

As raised by Limb and Dwyer (2001) it is often not possible to anticipate the dynamics that occur during fieldwork and the impacts our research may have. This was the case for the political situation that affected the way participants responded to observation of their home environments. We gathered direct observation data with minimal entry into participants' homes. The items observed were walls, window and door nets, compounds and drains, and the presence of vegetation. Where there was a need to enter homes or

communities with heads, we sought permission beforehand and we withdrew immediately from places where permission was declined, aggression occurred or participants were not willing to continue. The interviewers in the field were very experienced and managed these aspects effectively. However, this translated to incomplete household data and thus the sample size available for the study.

For the environmental investigations I conducted, I derived information from satellite imageries and existing secondary data sources. They did not involve any ethical issues.

4.13.3 Justice and Fair Treatment

As part of the incentive to participate, the respondents were offered a copy of the report delivered to them through their preferred media at the end of the research. Since then, copies have been made available to participants who showed interest and provided appropriate details to be reached. They were very happy with them.

4.13.4 Accounting for Anticipated Consequences of My Research and Reward for Participation

The questioning process raises issues for participants which they would ordinarily not think about. Often some questions and thoughts such as “*am I using the right prevention and treatment for malaria? What will happen to me when I have malaria and I don’t go to hospital? Is my environment risky?*” arise, for which the researcher is unprepared and must deal with during the fieldwork. Under such circumstances, I clarified my role as a researcher, shared the knowledge I had and advised them to seek professional help. Kobayashi (2001) and Valentine (2001) suggest sharing findings with participants as part of considering the wider consequences of my research.

As part of giving back, I fed my research findings back into LSMoH, the community and participants. I provided a feedback report to the participants suggesting household behavioural changes, such as using insecticide-treated bednets, and using personal protection when undertaking night-shift work to minimise human–vector contact. I also suggested covering water points, clearing vegetation and drains to eliminate stagnant water and reduce vector breeding sites. I shared my feedback report with the LSMoH Eko Free Malaria Project; it includes malaria infection trends over the years and reports of the household survey and policy recommendations. Apart from the aggregated malaria infection database which I fed back into the LSMoH to support their quest to improve their data quality and for public health decision-making, I did not share other datasets with them for ethical reasons.

4.13.5 Health and Safety for Field Workers

While we were conscious of ethical issues with the participants being researched, we also put into cognisance our own health and safety, as this was an important aspect to address prior to my obtaining ethical approval from Newcastle University and the Federal Ministry of Health, Abuja. We experienced several instances of aggression from participants and communities and in some instances we were taken to be government representatives, tax collectors, task force members etc. While we made efforts to clarify our roles and positions as researchers and field assistants by providing identifications, under aggressive situations we withdrew from the participants/communities even without completing our interviews. Often I received telephone threats which had consequences for following up participants or the request to withdraw during the follow-up stages. Participants' wishes to withdraw were always respected, and as indicated earlier, they were removed completely from the database analysis, and all paper copies of their questionnaires and direct observation protocol were destroyed. However, as the researcher who provides contact details on the information sheet, as ethically required, I am still faced with constant threats, from which I have no hiding place.

4.13.6 Ethical Approval

In addition to taking into consideration the above ethical principles, I requested permission to undertake the pilot study from the LSMoH and this was given for the project to be conducted under the Eko Free Malaria Project which already has ethical approval see Appendix IV. I acknowledge that I did not seek ethical approval from Newcastle University prior to commencing the pilot study. For the main study, I obtained ethical authorisations from the Nigerian Health Research Ethics Committee (NHREC) of the Nigerian Federal Ministry of Health (FMoH) and Newcastle University. The authorisations are attached as Appendices XV and XVI.

4.14 Conclusion

This chapter discussed the density approach implemented through GeoTIME to explore and visualise space-time patterns in malaria infection and identify a study location.

I further this by describing the two-phase cross-sectional study in Ikeja and Kosofe LGAs of Lagos state that was used to gather data on household's environmental and socio-cultural variables and malaria. The data gathering was made up of a pilot and main study. The pilot study used a mixed-methods approach consisting of a semi-

structured interview and pilot version of a questionnaire survey. The output from the pilot study was used to improve and feed into the development of a questionnaire that was administered by five interviewers in the main study.

In the main study, I administered a questionnaire survey, direct observation protocol, GIS and remote sensing methods to contextualise these households in Ikeja and Kosofe LGAs. In the same location, I examine the time-lagged relation between monthly malaria infection from 2000 to 2009 from health care facilities, and monthly climatic variables data on total rainfall, relative humidity and mean temperature for the same period from meteorological stations in Ikeja and Kosofe LGAs.

I highlighted some of the difficulties and ethical issues faced during fieldwork and some of the immediate actions that were explored to address them. As part of this chapter I discussed the data quality assessment methodology utilised to assess the malaria infection data gathered. The results are discussed in the next chapter.

Chapter Five: Quality Assessment of Malaria Infection Data

5.1 Introduction

Malaria has been in the international limelight for over a century because efforts at controlling or eradicating it have had little or no success. There are indications which show there has been a struggle with evaluating the impacts of malaria interventions. The reasons for this struggle being poor data quality and infrastructure in the most burdened country of which Nigeria is included (WHO, 2011b; 2012a; 2012b). Data of sufficient quality then becomes a concern for the disease. To address this quality in a harmonised manner, the Global Fund to Fight AIDS, Tuberculosis and Malaria (GFATM) in partnership with WHO and RBM has developed a GFATM Data Quality Assessment (GFATM DQA) tool (GFATM, 2009) to assess the quality of data arising on these diseases. When data is reliable, consistent, accessible and timely, we can evaluate the impacts of these interventions on the population of concern, monitor them and plan adequately for future interventions in the most effective manner and in so doing achieve a longer lasting cure.

In the last chapter, I discussed the methods used to generate and analyse a range of datasets on malaria and related environmental and behavioural variables. I highlighted the difficulties and ethics issues that arose during fieldwork.

This chapter is dedicated to assessing the quality of data on malaria infection as well as the system for collecting and reporting the data collected through the efforts described in the previous chapter and using an abridged version of the GFATM DQA tool. Abridged here means that, I have limited the scope of my summary questions and tasks and tailored the ensuing data collection approach to a way that is more flexible and less formal. Such a strategy was seen as necessary in order to breakdown the bureaucratic approach I sensed in the original version of the GFATM DQA tool kit and make it

useable for an individual researcher because if used in its original version it can hinder progress. Suffice it to say then, that the application of this methodology in my research is an imperatively exploratory one. The need to explore is largely due to an interest to evaluate the quality of the malaria resource generated by this research with no other tool than that developed to assess malaria indicators. The emergent results will highlight DQ issues and their implications for public health decision making and in so doing contribute empirically to the applied use of this tool. The chapter is thus structured around the methodology, the phases of implementing data quality assessment and the results of the efforts.

5.2 Methodology

The GFATM toolkit offers a step-by-step DQ assessment approach. Its methodology is grounded in the nine dimensions of data quality which are as follows: to address malaria as a public health concern, projects need accurate, reliable, precise, complete, accessible and timely data reports. Further to this, for data to be considered as having credibility and integrity, it must be consistent, confidential and minimise double counting.

As an initial step, I describe the conceptual framework followed by the range of DQ dimensions to be used, their operational definitions and the operational protocols through which the assessment is implemented.

5.2.1 Conceptual Framework

The conceptual framework in figure 24 is based on three theoretical foundations that describe the quality of data and that of the data management reporting systems through the dimensions of data quality. Firstly, the quality and functionality of the data management reporting system influences the quality of data produced and reported; secondly, the key functional components of a data management system, need to be in place at all levels of the data management and reporting system: the secondary health care facilities known here as service delivery sites (SDS) where the data is generated and partly aggregated and the reporting unit where the data is reported and aggregated at a state level here – the LSMoH Health Management Board; thirdly, high-quality data is produced and reported by a high-quality functional data management and reporting system. Meaning stronger systems produce better quality data and vice versa. These assessments are implemented using the dimensions of data quality.

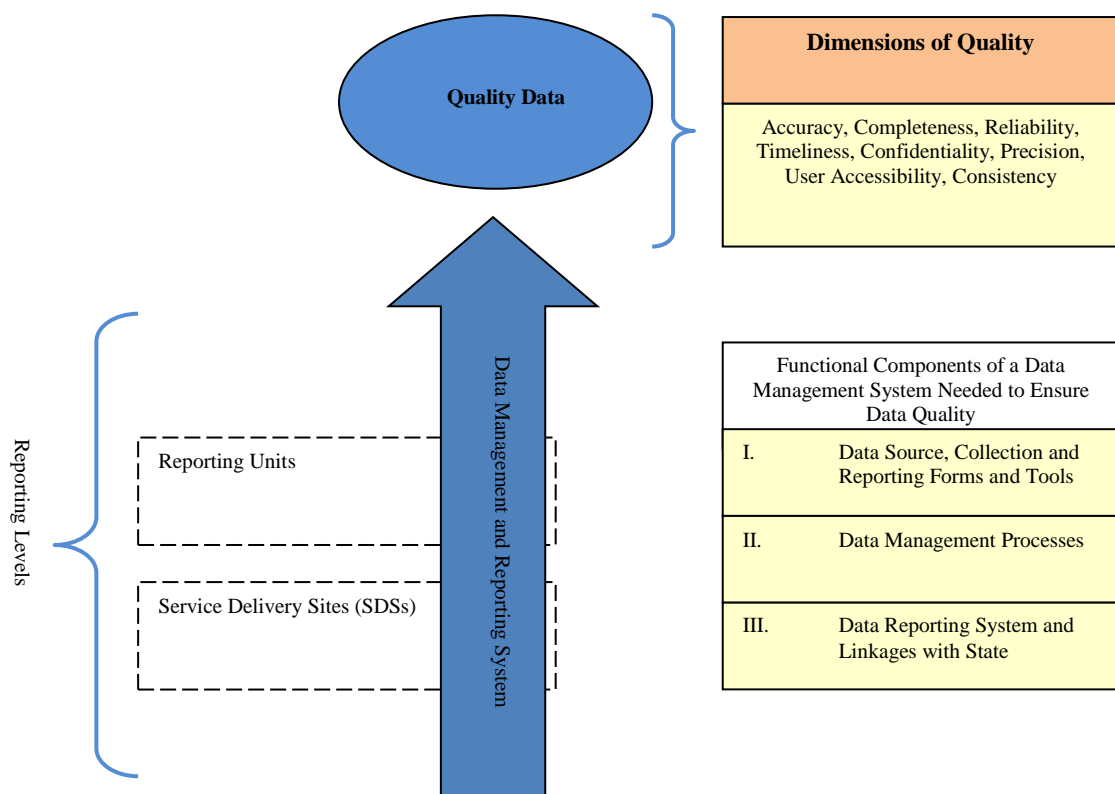


Figure 24: Conceptual framework for malaria indicator data quality assessment approach

Derived from GFATM (2009)

5.2.2 Operational Definition for the Dimensions of Data Quality

The DQ dimensions used in this research are accuracy, completeness, reliability, timeliness, precision, confidentiality, accessibility, consistency and double counting.

Accuracy: Data is accurate if it measures what it is intended to measure and shows validity, correctness and exists free of or with minimal error (Wand and Wang, 1996; GFATM, 2009). This includes errors arising from aggregation and recording.

Completeness: Completeness measures the extent of under or over reporting in data that can lead to false alarms (Tayi and Ballou, 1998; Devillers and Jeansoulin, 2006; GFATM, 2009).

Reliability: Reliable data is that data that is consistent irrespective of who collects it. Thus the same system and method of data collection has been adopted. It is objective by being unbiased, unprejudiced, impartial, free of manipulation, credible and highly regarded (Wang and Strong, 1996; Pipino *et al.*, 2002; GFATM, 2009).

Timeliness/time related dimension: Timeliness is assessed by the currency of data at the reporting unit and the frequency at which they are updated (Wang and Strong, 1996; Batini and Scannapieco, 2006; GFATM, 2009).

Confidentiality: This assesses the extent to which data is managed, restricted and kept secure thus protecting personal data from being disclosed inappropriately (Wang and Strong, 1996; GFATM, 2009).

Precision: This describes the level of details that the malaria indicator data has. For example additional details like gender, age, address etc. and how these details are linked to the malaria data.

Accessibility: This is the extent to which data are available, easily or quickly retrievable and this can be estimated as a function of costs, time frame, format, standards, copyright, available technologies and the ability of a data user to access data (Wang and Strong, 1996; Batini and Scannapieco, 2006; Devillers and Jeansoulin, 2006).

Consistency: The extent to which data are always presented in the same format, are compatible with previous data and match the state of the real world (Wang and Wang, 1996; Wang and Strong, 1996).

Double counting: Though this is not a well-used or known dimension of data quality, it has implications for representativeness, accuracy, reliability and integrity. The existence of double counting will have implications for the mentioned dimensions of quality.

Based on these dimensions of data quality, the DQA comprise two components: the assessment of data management and reporting systems; and the verification of reported data which will be implemented through the System Assessment Protocol (SAP) and Data Verification Protocol (DVP).

5.2.3 System Assessment Protocol

The purpose of the system assessment protocol (SAP) is to identify potential challenges to data quality created by the data management and reporting systems at two levels: the service delivery sites (SDSs) and reporting units as shown in figure 24. The SAP relies on summary questions (Appendix XIII). I developed these questions to assess three functional areas (Figure 24): data source, collection and reporting forms and tools; the data management processes and the data-reporting systems and their linkages. This will describe confidentiality, reliability, precision, consistency, double counting and

timeliness attributes of the LSMoH data management and reporting system. At the end of the assessment, I will identify strengths and weaknesses for each of the functional areas and its implications for the quality of malaria data produced. This aspect of the research takes place on site at the selected SDS and reporting unit.

5.2.4 Data Verification Protocol

The purpose of the data verification protocol (DVP) is to assess, using qualitative and quantitative methods and on a limited scale, if SDSs and reporting units are collecting and reporting data that measure the malaria infection accurately and on time, and to cross-check the reported results with other data sources. This protocol is based on quality dimensions such as accuracy, reliability, and completeness as outlined in figure 24 and its corresponding summary questions/tasks I developed in Appendix XIV.

To do this, I determine if a sample of the SDSs have accurately recorded the activity related to malaria infection on source documents. I use a bottom up approach as used in GFATM (2009) to trace the data starting from the lowest level SDS up to the reporting unit to see if it has been correctly reported at the reporting unit (highest level). This exercise takes place in two stages: at the selected SDS and followed up at the reporting unit.

5.2.5 Data Collection Methods

As part of the field work conducted between March and June 2008, I visited the SDS and reporting units to gather malaria infection data and during this period also gather data on its quality through participant observation of work practices, conversations, informal interviews and review of existing documents including ICD registers. It took a period of 8 weeks to extract malaria infection data manually from registers. The process of extracting malaria infection data was done with the aid of medical record officers. Whilst this was being done, informal interviews were concurrently held with three medical record officers at the LSMoH as well as two officers who are heads of reporting units. The purpose of the informal interviews was to seek responses to the summary questions and tasks pertaining to the quality of data. The informal interviews were in form of everyday conversations and enquiries about the data being collected. The conversations and enquiries were ongoing throughout the data collection period.

My tasks as participant observer and researcher working alongside the medical records officers, were as follows:

- Sourcing ICD registers from immediate storage and archived locations
- Collating available data from ICD registers
- Updating submission records of SDS
- Observing work practices
- Probing key informants (medical records officers and heads of department) through informal interviews, everyday conversations and chats with regards to summary questions in Appendices XIII and XIV
- Reviewing documents and following up initial assessments
- Verifying collated data through qualitative methods
- Assessing data based on the dimensions of data quality as identified earlier.

I gathered data on selected Lagos state SDSs that have been in existence since the year 2000. Eighteen SDSs that met this criterion had their data evaluated at the reporting unit, while another one, selected from these 18 SDSs, also had both its data and part of the data collection reporting and management system evaluated at the SDS level. The emphasis is on inpatient and outpatient data on malaria infection collected and reported between 2000 and 2009 in secondary HCFs within Lagos state.

5.2.6 *Quality Assessment*

I employed both qualitative and quantitative approaches in my data quality assessment. In order to verify data for internal consistency, accuracy and reliability, I used a bottom up approach (GFATM, 2009) to trace, compare and cross check data collected onsite at SDS with data at reporting units for that selected SDS. The method for tracing accuracy and reliability of data is by cross checking and tracing submitted totals at reporting unit with monthly entries and totals which exists at the SDS. I performed accuracy and reliability checks for selected years between 2000 and 2009 which had complete monthly datasets for the whole year. I did not check the source document at the SDS for confidentiality, accessibility issues and ethical consideration but gathered this information from the interviews and conversations I had with the medical records staff. The cross checks are to compare monthly data aggregated at the SDS level and the same data reported to the reporting unit. The outcomes of these assessments are presented graphically, quantitatively and discussed qualitatively.

In the next section, I present the way in which the GFATM DQ Assessment was implemented beginning from the selection of sites to the analysis and review of results.

5.3 Implementation of the Malaria GFATM DQ Assessment

There are constituent steps and the actions to be carried out in order to implement the GFATM DQA, from the location of data collection, to its assessment, analysis and then the report writing. For clarity and repeatability, I divided the process of implementing the GFATM DQA in four phases (figure 25).

5.3.1 Phase One

Phase one consists of six steps that describes the bureaucratic procedures required to do field work in Lagos state, preparation and planning stages prior to data collection. These steps took place at multiple sites (Newcastle, United Kingdom and Lagos, Nigeria).

I worked with malaria infection data as the indicator of choice as it aligns with the primary focus of my research as well as it being the most appropriate indicator for highly endemic areas (Remme *et al.*, 2001) and is currently used by the Nigerian National Malaria Control Program (NMCP) (FMoH-NMCP, 2008). Lagos is my case study location where I sought permission and ethical clearances all as explained in the previous chapter.

I worked with the Lagos State Ministry of Health (LSMoH) as custodians of malaria data from the state's HCFs. While I assess the whole health system's ability to manage and report data, I specifically assess the quality of data generated from only the secondary HCFs as source because they are the only ones with a capacity to collect and report data. I have selected to work with the reporting period between 2000 and 2009 to correspond with the scope of the research and as also advised by my supervisors and LSMoH to coincide with the period when the likelihood of available data is higher. I chose all SDSs with reporting capability that correspond to this period for overall quality assessment. Any SDS that was established after 2000 was not included. I selected only one SDS purposefully for more detailed onsite data verification assessment. I also chose to work with only one reporting unit Health Services Commission (HSC) where I received permission to access data. The SDS and reporting unit have been purposively selected (GFATM, 2009) and for ethical reasons I do not name the chosen SDS.

I visited the SDS and the reporting units to familiarise myself with the processes and working culture in order to support the development of data collection instruments. I designed the malaria infection template (appendices XI and XII) described in the previous chapter to gather the infection data. I reviewed and modified my summary

questions (appendices XIII and XIV) to suit the participatory approach I employed. I reviewed documents on site and had informal conversations with the medical records officers and this was ongoing throughout the eight-week data collection period. I recorded these conversations and interviews in a notebook which I reviewed daily with the staff I worked alongside with.

5.3.2 Phase Two

Phase Two which concerns the assessment of the data reporting system took place at the Health Services Commission (HSC) reporting unit. It consists of two steps: to assess the LSMoH Data Management Systems where I implemented quality dimensions associated with the SAP. In the second step, I traced and verified malaria infection data reported by reviewing the reports for the selected reporting period submitted by lower reporting levels which are the SDSs to confirm if inpatient and outpatient figures, totals etc correspond as well as compare with reports from the laboratory. I implemented the quality dimensions associated with the DVP.

5.3.3 Phase Three

I carried out phase three at the SDS and the constituent tasks were similar to the tasks performed in phase two. While I assessed the data management and reporting system at the selected Service Delivery Sites by determining if a functioning system is in place to collect, check, and report data to the next level of aggregation (Step 9) implementing the SAP, I also traced and verified malaria infection data to reported results from SDSs (Step 10) implementing DVP.

5.3.4 Phase Four

In phase four, I consolidated the assessment of the data management and reporting system at the SDS, and reporting units. This was carried out at multiple sites (reporting units, SDSs and in the UK). The tasks included analysing statistics, answering the summary questions, clarifying initial assessment and responses with the staff, sharing my preliminary findings with them and reaching a consensus on them. I shared the final results with the LSMoH.

In the next section, I present the results of the exercise and I have structured it according to the functional area and dimension of data quality that they address.

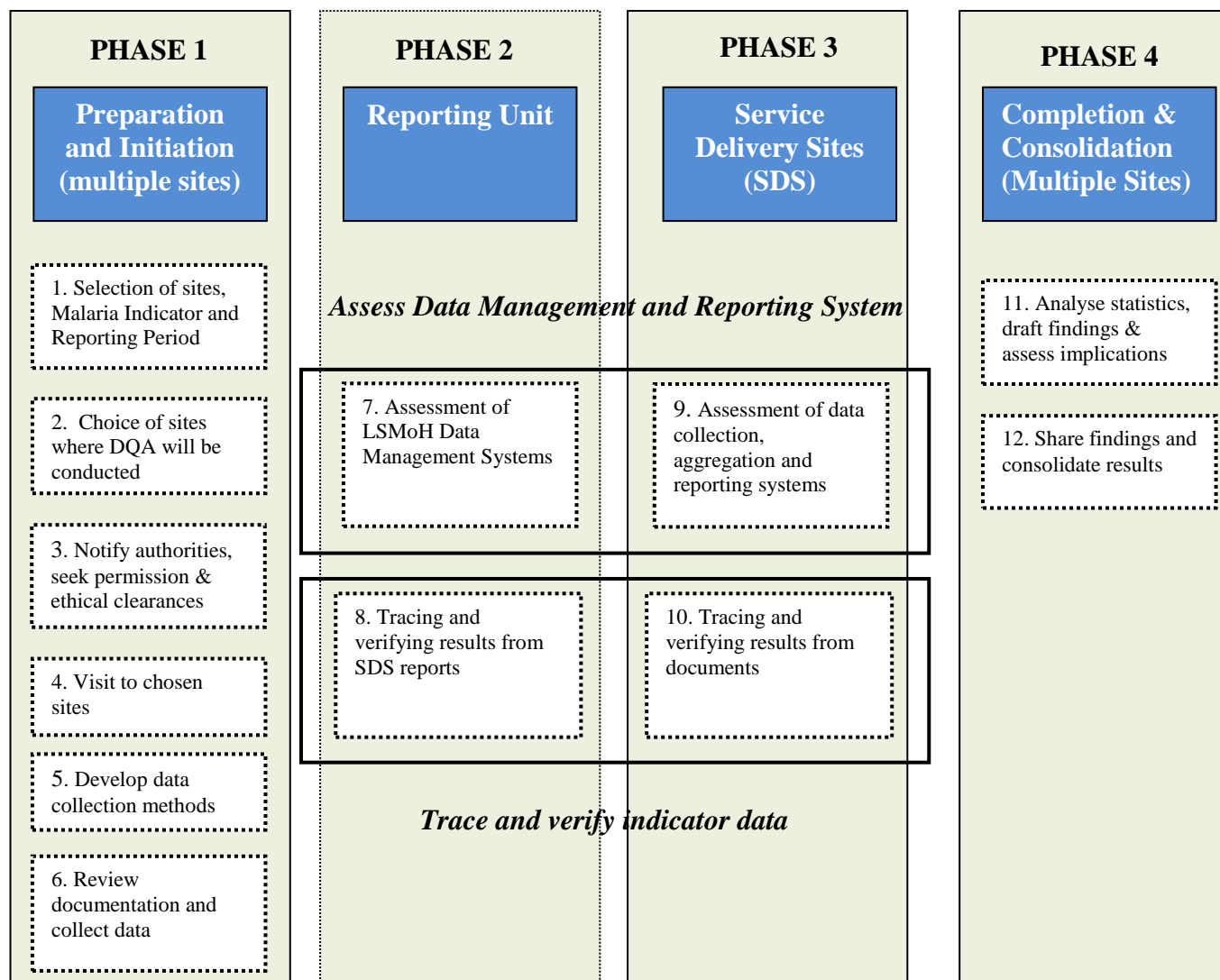


Figure 25: Phases in the Quality Assessment of Malaria Indicator Data

5.4 The Assessment of Data Management and Reporting System

To assess the quality of the data management and reporting system is to examine the malaria data source, collection and reporting forms and tools, the data management processes and the linkages of the data-reporting system used at the SDSs and the reporting units of the LSMoH. I respond to this by applying the summary questions of the systems assessment protocol in Appendix XIII, and in so doing obtain answers to eight dimensions of quality: reliability, consistency, precision, accuracy, confidentiality, timeliness, accessibility and availability.

5.4.1 Data Source, Collection and Reporting Forms and Tools

The LSMoH has identified medical records as a standard data source document for identifying and extracting patients' malaria diagnoses. It has also recognised the diagnostic index card (DIC) and the disease register for collecting and recording disease outcome for in and outpatients respectively. The International Classification of Diseases and Related Health Problems (ICD-RHP) register has been identified as the standard reporting document for reporting monthly statistics on malaria to the LSMoH reporting units. These forms and tools have been recognised by the LSMoH as standard documents used across all its SDSs.

The medical record is the source document used to register a patient's past and present health visits to the HCF and any family history of disease. The DIC is characterised by rows and columns. It is used to record the primary disease and any complications arising, hospital registration number of the patient, address, age, gender, doctor and disposal status (i.e. if the patient has improved, been discharged, died, or their body is in the mortuary, etc.) extracted from inpatient medical records. The disease register is fashioned after the features of the DIC and used only to record outpatient occurrences of malaria, extracted from medical records.

The ICD-RHP is the standard diagnostic tool used to classify diseases and other health problems recorded on many types of health and vital records, including death certificates and health records (WHO, 2011a). The LSMoH SDSs have developed a paper register fashioned after the ICD-RHP and has a list of all diseases including malaria. In the register, malaria is recorded under protozoan diseases classified against the category of "Infections and parasitic diseases". Unconfirmed malaria cases are classed under "unspecified malaria" which means clinically diagnosed malaria cases without parasitological confirmation. The register has rows and columns for recording

counts and mortality from the disease. The period of this study (2000 to 2009) witnessed two versions of the ICD-RHP register. Between 2000 and 2002 ICD-RHP was adapted from the ICD-RHP version 9 (Figure 27) and it featured monthly counts of and mortality from malaria by gender, in- and outpatient status. The ICD-RHP register used between 2003 and 2009 is adapted from ICD-RHP 10 and features disease classification by gender, age group, parasite types, in- and outpatient status.

The standard forms and tool are used at appropriate levels. For example, when a patient attends an SDS and shows symptoms associated with malaria, these symptoms, treatment protocols and outcome are recorded in the patient's medical record by the medical doctor. The clinical coding staff primarily extract the malaria data from the patients' (in and outpatient) medical records and record it in the DIC and disease registers for in and outpatients respectively. In instances when malaria has not been directly diagnosed by the medical doctor, the medical records officer deciphers this from the patient's recorded symptoms and the doctor's prescription. The extraction and recording of malaria data is a daily routine of the medical records officers at the SDS.

At every month-end, the medical records officers at the SDS extract and transfer the total number of in and outpatient cases of malaria alongside other diseases recorded in the monthly ICD-RHP register. This is marked with the name of the SDS and time of reporting, and submitted by each SDS to two reporting units of the LSMoH. All malaria case data sourced for this research was extracted from the ICD-RHP registers at the reporting unit. Physical evidence from the reporting unit showed that over 95% of the SDSs use the ICD-RHP registers. Delay in changing from ICD-RHP version 9 to version 10 was noted in some SDSs.

LAGOS STATE HOSPITALS MANAGEMENT BOARD
MONTHLY RETURNS OF DISEASES AND DEATHS
 (According to Basic Tabulation List of the ICD 9th Edition)
 IN PATIENTS/RESIDENTS

MONTH OF JULY 2002

Basic Tabulation List	Cause Group	Cases		Deaths	
		M	F	M	F
01	INFECTIONS AND PARASITIC DISEASES				
010	INTESTINAL INFECTIOUS DISEASES (001-099)				
010.1	Cholera				
011	Eimeritis and Other Diarrhoea Diseases				
012	Typhoid Fever				
013	Shigellosis				
014	Food Poisoning				
015	Amoebiasis				
	Intestinal Infections due to other Specified Organism				

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Figure 26: Pre-2003 International Classification of Diseases and Related Health Problems (ICD-RHP) register

5.4.1.1 Precision and Details Level

The precision with which malaria data has been measured has followed the characteristic of the ICD-RHP template used and thus varied within the period of this study (2000 to 2009). Between 2000 and 2002, malaria cases and deaths were recorded by gender, in- and outpatient status. Details of age of patient and parasite type were not reported; from 2003 the data included these: age group (<1 year, 1 to 4 years, 5 to 14 years, 15 to 49 years, and > 50 years), malaria parasite type (*Plasmodium falciparum*, *P. Vivax*, *P. malariae*, *P. Ovale*), and whether severe malaria-like cerebral malaria and/or malaria in pregnancy. Even though there was often missing data, 95% of the 18 SDSs studied conformed to reporting these details on the ICD-RHP register after 2003 while the remaining 5% still employed the pre-2003 approach.

During the field verification to confirm the status of malaria data in private health care facilities, it was revealed that they do not have a standard source or reporting document because they have not been mandated by law to report health data. However, the current government has noted the implications of this in estimating the true burden of the disease in the population. There are discussions by the LSMoH to train members of the private health sector in data reporting and also to change policy to mandate them to start reporting data.

5.4.2 Data Management Processes

This section will discuss challenges to data quality, storage and archiving issues and how they affect accessibility to data as well and maintaining confidentiality guidelines with malaria data.

5.4.2.1 Challenges to Data Quality

Some of the main challenges identified to malaria infection data quality are

- Data storage and archiving system
- Lack of staff, high workload and low funding
- Timeliness
- Data sharing
- Redundancies and uncoordinated data collection
- Discrepancy in data reported
- ICD precision
- Cross-checks with lab reports not reliable, since labs take outside patients

5.4.2.2 Data Storage and Archiving System

The use of the paper-based ICD-RHP register for reporting, storage and archiving has become a problem at the SDSs and LSMoH reporting units over time, as they are not converted into electronic copies, but filed in paper files inscribed with the name of the reporting SDS, year and month. The files are stored on bookshelves, stacked in a corner of a room, and data pre-dating 2003 is kept in a distant storage room, in often neglected and deteriorating conditions with no archiving system, such that accessing older data becomes a Herculean task. Figures 28, 29, and 30 show, a snapshots of storage and archiving locations for disease data.

As noted during fieldwork, the collection of malaria indicator data by LSMoH has been a long-term and ongoing process and that data that date back to the 1990s still exists. However, because there is no appropriate way of archiving this data, at some point in time it becomes forgotten, threatening availability for present and future use. Also because the data is still in paper format, converting it into a digital format has major time, human and cost consequences for any user. These costs as I learnt during the course of my PhD research influence access to data required for research and planning purposes. Some of the reasons raised by the staff for lack of computerised storage are the erratic power supply and printers, and lack of skilled manpower to handle this change.



Figure 27: Storage place for archived malaria data



Figure 28: Access conditions to malaria data storage archives



Figure 29: Stored condition of archived malaria data

5.4.2.3 Confidentiality Issues and Standards in Management of Malaria Data

The LSMoH and selected SDSs show a high level of integrity in maintaining confidentiality of patient records to external parties according to the results of observations, experiences and interview about this theme. At the SDS only the members of staff who are required to extract clinical codes have access to patients' medical records. They report only aggregated records of malaria infection data that are without

personal identifiers or links to patients' records. These efforts show compliance with expected national and international standards.

5.4.3 *The LSMoH Data-reporting System and its Reporting Linkages*

This section discusses data-reporting avenues, describes the state reporting system linkages and explains how multiple monthly patient visits are recorded, as well as timeliness issues.

5.4.3.1 Data-reporting Avenues and Units

The LSMoH data-reporting system is made up of four reporting units that occur at two state administrative levels. They are the Health Management Information Systems (HMIS) unit, Health Services Commission (HSC), the Vector Control Unit (VCU) and the Monitoring and Evaluation (M&E) unit. HMIS, HSC and VCU operate at the state administrative level while the M&E unit operates at the local government level. Figure 31 shows the LSMoH data-reporting system, and highlights expected and actual reporting avenues and units and how they all link together to form the Lagos state data-reporting system. The expected reporting avenue is that all community health posts, primary HCFs, and SDSs in each local government area report malaria infection data to the M&E unit, which then forwards it to the HMIS, while the HSC receives data from the SDS alone. The state tertiary teaching hospital reports directly to the HMIS unit. The VCU gathers and hosts only malaria intervention data. Despite the fact that the primary HCFs and the community health posts are expected to report data through the M&E unit to the HMIS unit, they do not presently perform this role due to being ill-equipped to collect or report data.

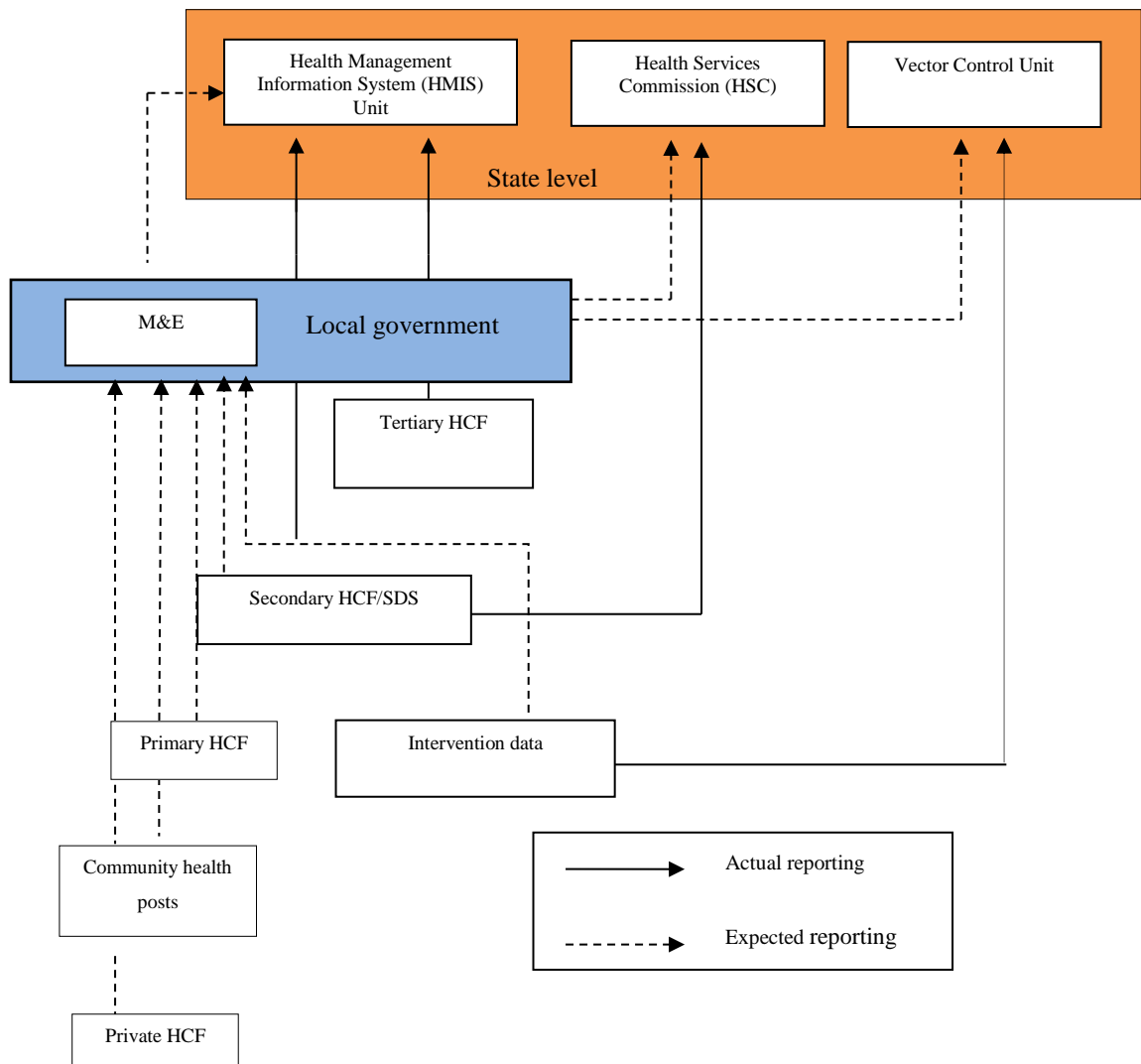


Figure 30: Lagos State Ministry of Health malaria data-reporting system and structure

5.4.3.2 Linkages of HCFs to the State Reporting System

Even though the data collection and reporting system of the LSMoH appears seamless according to Figure 31, in many instances data reporting is duplicated and reporting channels boycotted. Many private health care facilities exist, some of which are registered and others operating without a licence. Registered private HCFs are supervised through the M&E unit at the local government level, but they are not mandated or monitored by law to collect and report data, despite the fact that many residents of Lagos are privately treated. The SDSs with capacity to collect and report malaria data boycott the M&E office in reality, even though they are mandated to report to it, and instead report directly to the HMIS and the HSC at state level. The reason

given is the inability of the M&E unit to handle the large volume of data generated by the SDSs. The Lagos state teaching and research hospital (tertiary HCF), reports directly to the HMIS. They are not expected to and do not report to the HSC or the M&E unit. None of the SDSs, primary HCFs and the community health posts report to the VCU. The VCU manages only intervention data; they do not have the wide coverage of data collected by the HSC and the HMIS unit.

As shown in Figure 31, there is an expected and defined data-reporting channel and link to the state reporting units, and actual reporting (represented by bold lines) is clearly different from expected reporting (represented by dashed lines). This signifies a broken reporting link between the M&E unit and the state reporting units. With the VCU hosting only intervention data, there is obviously no clear or defined reporting channel between the VCU, the SDS and the other state reporting units. Also, the horizontal and vertical connections and communications between the Lagos state HSC, VCU and HMIS unit are unclear and undefined. There is no link or communication with private HCFs, community health posts and primary HCFs in the reporting linkages, despite these being much used services in communities, especially for common illnesses like malaria. In summary, data-reporting channels are not seamless and data reporting is usually duplicated.

5.4.3.3 Double Counting and Duplication of Data

Double counting is avoided at the SDS by recording only one instance of a type of disease for a patient in a month even if the patient visits more than once. In instances when the patient visits the SDS more than once in a month for the same illness, it is noted as a follow-up treatment and not a new occurrence of the disease.

However, double counting happening across SDSs for the same patient is not addressed. If the same patient visits two different SDSs for malaria treatment at the same time or in the same month, there is no linking system to identify the same patient with the same disease or receiving the same treatment at different SDSs. It is noted that with outpatients who visit an SDS, there is the possibility of loss of follow-up, and across SDSs there exists the possibility of double counting. This occurs due to the lack of connection between patient case histories for patients using multiple HCFs

Only the status of inpatients is noted at the SDS of the patient's last visit. This is done through the disposal status detail recorded in the patient's medical record (i.e. if the patient has improved, been discharged, died, or their body is in the mortuary, etc.) and

in the DIC. This information is collected only for inpatients because the SDS is responsible for them by law. It is not recorded for outpatients unless they are dead and their bodies brought to the SDS, and their cause of death is confirmed to be malaria. They are, however, still not treated as a malaria patient of that SDS because the death did not occur there.

5.4.3.4 Timeliness

Observations at the reporting units show that SDSs often report their malaria data after the submission cut-off date. As the report submission is done via the paper ICD-HRP register and not online, the main reason cited for late reporting is the geographic location of the SDSs. Most SDSs situated on the outskirts of Lagos and classed here as rural, experience this difficulty to a great extent.

Table 6: Timeliness reporting in 2008 according to location of SDS

	Early	Late
Urban	9	2
Rural	1	6

Table 6 shows the reporting timelines of SDSs in 2008 classified by their location. A total of six out of eight late reporting SDSs are situated on the outskirts of Lagos, and only one out of ten SDSs reporting early is situated in close proximity to the reporting units. Late reporting stems from the lack of human and economic resources to meet the reporting deadlines and make periodic journeys to submit the monthly report. Often, SDSs situated on the outskirts of Lagos accumulate their reports and send them out only once or twice per annum.

5.5 Quality Assessment and Verification of Reported Malaria Infection Data

I assessed the quality of malaria infection data for the 18 SDSs reporting to the LSMoH during the period between 2000 and 2008 for completeness, accuracy and reliability by responding to the data verification protocol in Appendix XIV.

5.5.1 Completeness

I analysed the completeness of the malaria data at the reporting unit over the period of 2000 to 2008 for the 18 reporting SDSs. According to Figure 32, the routinely collected data is characterised by missing data, and no SDS reported complete malaria infection data during this time period. The data for the majority of the reporting SDSs was 50%

or less complete, and only one SDS, located in the urban area, had data with completeness level as high as 70%. One of the SDSs located in the rural area had no complete data for the time period. Also, I plotted the status of completeness of malaria infection data for all SDSs over the period of 2000 and 2008. According to the figure 33, data completeness diminished from 2000 until 2003, when completeness was at its lowest (0%). One of the reasons given is that it coincided with when improvements in medical records keeping were being implemented, but the period was burdened with inadequate number of staff, the delay in training staff and making available resources needed for gathering a greater level of details (in terms of precision) being collected on patients. From 2003, data completeness improved and increased consistently over the period studied. In 2008, over 80% completeness was recorded, signifying a great improvement by the SDSs.



Key: U= Urban R= Rural

Figure 31: Percentage of monthly reports expected from SDSs, 2000 to 2008

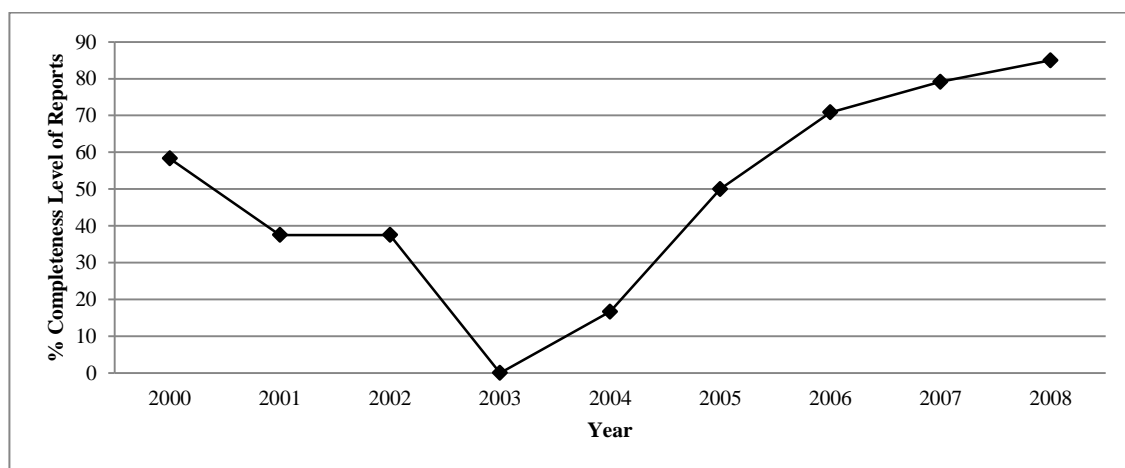


Figure 32: Percentage of monthly reports expected from SDSs, 2000 to 2008

5.5.2 Accuracy and Reliability

Figure 34 shows both the tracing and verification method applied to check internal consistency and accuracy for malaria infection data under the LSMoH and the results of this effort. I assessed accuracy using a top-to-bottom approach, by tracing data at the reporting unit down to the same data at the SDSs that reported it. I selected 2007 as the sample year for the SDS chosen, because it was the only year with complete datasets at both the reporting unit and the SDS. Figure 34 shows accuracy issues with the monthly and annual total cases for malaria infection between those reported and values registered at the SDS. A total of 496 inpatient cases for malaria infection were reported at the reporting unit; however, there were 500 cases registered in the records of the SDS. At the reporting unit 21,215 cases of malaria infection in outpatients were reported, which is over 7,500 cases higher than the value recorded at the SDS, at 13,674 outpatient malaria cases. The annual total number of malaria cases reported in 2007 is 21,711, while at the SDS only 14,174 malaria cases were recorded, demonstrating accuracy issues and discrepancies.

5.5.3 Reliability

When accuracy issues as noted above arise, then reliability of the data is put to the test. I compared inpatient malaria records with malaria laboratory records at the SDS between 2000 and 2008. The results were inconsistent, but this did not mean they were inaccurate. The laboratory services are used by both in- and outpatients as well as commercially by other HCFs, and they do not differentiate between inpatients, outpatients and outsiders. This inflated the numbers, causing discrepancies in the reports.

5.6 Discussion

From the foregoing assessment of the data management and reporting system, I noted that there exists a structure, but with linkages that are often not used. The LSMoH can boast of long-term archived data, though not in easily accessible formats and faced with the danger of destruction due to poor storage conditions. Should this data be made efficient through digital conversion, by investing in appropriate manpower and IT resources, it would be a significant and reliable resource in evaluation studies to assess the impact of intervention on malaria incidence in Lagos state. This would generally help to improve issues of consistency, reliability, late reporting, levels of precision, double counting and broken linkages, as noted in the assessment. It would improve

accuracy and support the improvements noted in the data completion and missing data statuses of the SDS over time, particularly since 2003, when they began gathering and reporting more precise details for malaria infection data. Help is needed in this direction to support the LSMoH achieve this objective, as using poor quality data for public health decision-making or research data has a number implications that is reflected in the use of this data for this research.

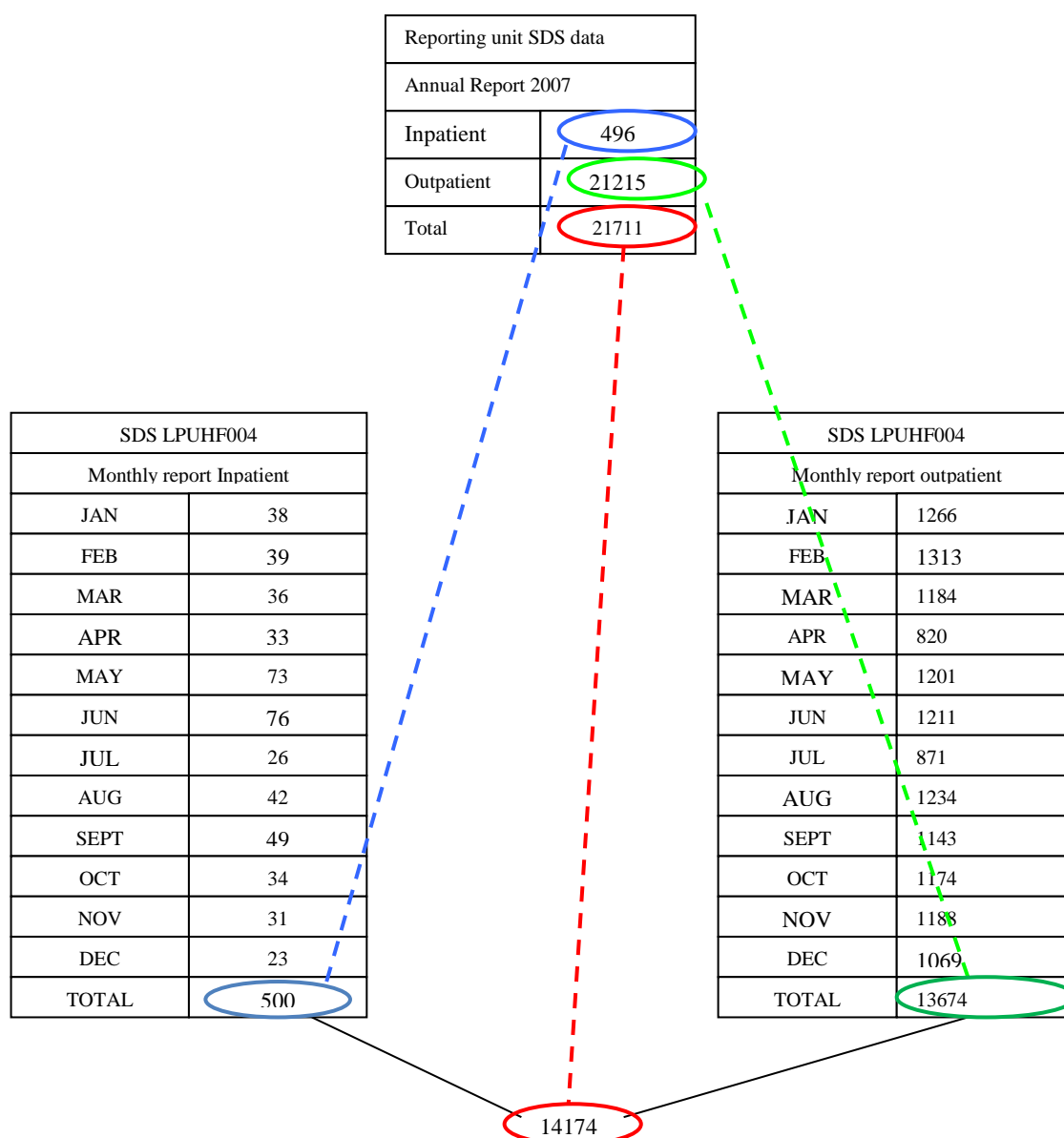


Figure 33: Accuracy assessment for 2007 malaria infection data at reporting unit and SDS

In this research, I could only infer elevated disease rates for local government areas by assuming that all malaria infection data generated from the HCFs are from patients living in the LGAs where the HCFs are situated, even though I know that this is not

always true. Patients may prefer to use HCFs nearer their places of work than those nearer their homes, so that SDSs situated in working districts report high rates of malaria infection. The missing data from reporting SDSs and the fact that private HCFs, community health posts and primary HCFs do not report data means that I cannot exploit the full potentials of the data resource that would have been available for the location. Monitoring temporal trends is problematic, such that rather than look at the numbers of cases and level of disease, I look more at the proportion and pattern.

The overall quality assessment of malaria data has given an insight into the system that produces the data and the data produced. This has highlighted some of the issues that drive the need to use this data by focusing on other aspects of the data, such as proportion, and less on level, as well as focusing on developing a baseline information system, which is a product of this research that can be improved with future research.

5.7 Conclusion

This chapter has described the quality of malaria infection data used to build and populate a spatio-temporal database in order to analyse space-time patterns of malaria infection in Lagos state as well as to assess its relationship with climatic variables. While data quality issues with the data and reporting system have been identified and described, the data will still be used in this research to respond to the research objectives. It will also be used bearing in mind that data reported has no geographic bearing on the patients diagnosed; rather, the focus of the research will be on malaria infection at place of reporting and not place of occurrence.

While LSMoH is to be applauded in its efforts made in data reporting, more work needs to be done on establishing an archive, recording, storing and submitting data digitally to improve timeliness, particularly for HCFs in rural areas and access, encouraging the private sector HCFs to report data, while also building up manpower to undertake these tasks successfully.

The next chapter is concerned with the examination of space-time patterns in the spatio-temporal malaria infection database developed in this study, using GeoTIME, a new geospatial tool designed to identify and visualise patterns.

Chapter Six: Exploratory Space-Time Patterns of Malaria and Examination of its Relationship with Meteorological Variables

6.1 Introduction

From the previous chapter, I acknowledge some of the weaknesses of the malaria infection data and recognise the need for the data providers to do more with respect to quality issues that will preserve the longevity of the data for public health decision-making. I also recognise the efforts undertaken as part of this research to gather, extract, convert and process over 15,000 paper records of raw malaria data into digital format that has now been built into a spatio-temporal database and employed in this thesis. The data is often characterised by huge gaps in reporting and as such can present interpretability issues when utilised in core analysis, as experienced in this research.

In this chapter, therefore, I utilise this data to respond to research objectives two and three. Objective two is to explore and visualise the spatial and temporal trends of clinical malaria infection cases at HCFs in Lagos state. Through this analysis I identify HCFs with differing elevated disease rates such that their locations become a focus for further in-depth study.

Objective three is a pursuance of the results emanating partly from objective two: a study site that will become the focus of this analysis and others. I examine the relationship between clinical malaria infection and meteorological variables in a specific location of Lagos (Ikeja and Kosofe LGAs) with elevated malaria infection rates and selected on the outcome of research objective two, as well as the consideration of its ecological characteristics.

The chapter is divided into two broad sections, firstly examining and visualising spatial and temporal trends in clinical malaria infection in Lagos state and the identification of locations where the HCFs report elevated cases of malaria infection. This section is presented as an interim result which feeds into the selection of a study area that leads to the second section and subsequent chapter. The second section focuses on assessing the

relationship of malaria infection and meteorological variables in a specific location (Ikeja and Kosofe LGAs) characterised by high malaria infection rates and diverse ecological characteristics.

6.2 Exploration and Visualisation of Temporal and Spatio-Temporal Patterns in Clinical Malaria Infection in Lagos State

In this section, I study the spatial and temporal trends in clinical malaria reported at state level by utilising a qualitative approach to assess the temporal patterns in different population groups. I further implore the exploratory and geovisualisation capacity of GeoTIME to search and visualise space and time patterns in an integrated form. GeoTIME offers a relatively new and flexible approach to identify and explore space and time patterns in malaria cases in a 3D space-time cube (Oppong and Harold, 2009).

6.2.1 Temporal Patterns of Clinical Malaria Infection in Vulnerable Populations

I examine the temporal patterns of malaria infection in vulnerable populations (pregnant women and children below the age of five). The data explored in this case is not differentiated by health care facility but rather collated at state level by the LSMoH. Owing to data availability issues, this aspect of the study focuses on the period between 2006 and 2009.

Figure 35 shows the temporal patterns of clinical malaria infection in pregnant women between 2006 and 2009. Overall, one sharp peak and two dips occur in the number of malaria infection cases, reported in August 2007, December 2006 and April 2007 respectively. Between 2006 and 2007, the pattern is irregular and characterised by sharp increases and decreases and between September 2007 and December 2009, and then the rise and fall patterns in reported malaria cases become more regular.

In January 2006 about 50 cases of malaria in pregnant women were reported. This decreased to 20 malaria cases in July of the same year, after which it increased again and then plateaued at about 70 cases between October and November 2006. In December 2006 a sharp reduction to less than 30 cases occurred and then it rose sharply to over 100 cases in January and March 2007. In April 2007 the number of cases reported plummeted to less than 20 cases and rose sharply again to over 150 cases in May 2007. The number of pregnant women infected with malaria shot up again in August 2007 to over 270 cases, after which there was a sharp decline in cases reported. From November 2007, the regular pattern in the rise and fall of malaria infection cases in pregnant women continued ranging between 75 cases to 140 cases until December

2009. This was a period of intense house-to-house interventions with implications for lower malaria records. Prior to November 2007 the transition between governments made access to resources and intervention programs difficult and unreliable with implications for data reported.

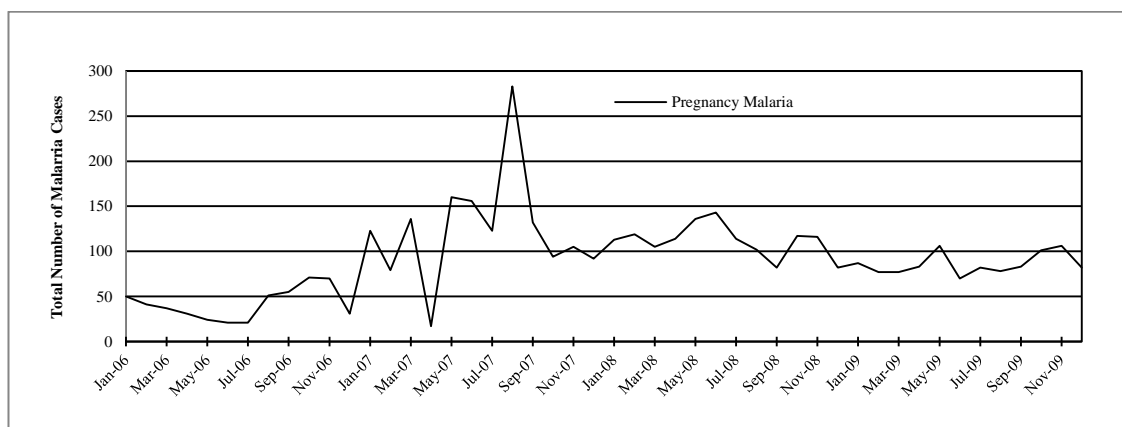


Figure 34: Total number of pregnancy malaria cases per month according to LSMoH, 2006–2009

Figure 36 shows that the temporal pattern in children less than five years old (paediatric malaria) between 2006 and 2009 is irregular, but at some point between June 2008 and December 2009 becomes cyclical, characterised by sharp peaks and dips. The lowest number of paediatric cases occurred in January 2006, while the highest occurred in September 2008. High numbers of paediatric malaria cases also occurred in November 2006 and 2008, and March and May 2009. Paediatric malaria infection increased steadily from about 1,000 cases in January 2006 to over 1,500 in May 2006, and decreased immediately to rise steadily from July 2006 to about 2,300 cases in November 2006. From June 2007 to July 2008, coinciding with the house-to-house and school intervention era, about 1,200 cases of malaria were regularly reported per month, after which sharp rises and falls in cases consistently occurred until November 2009. The pattern noted in this latter period was due to erratic funding for the school-based aspect of the intervention project.

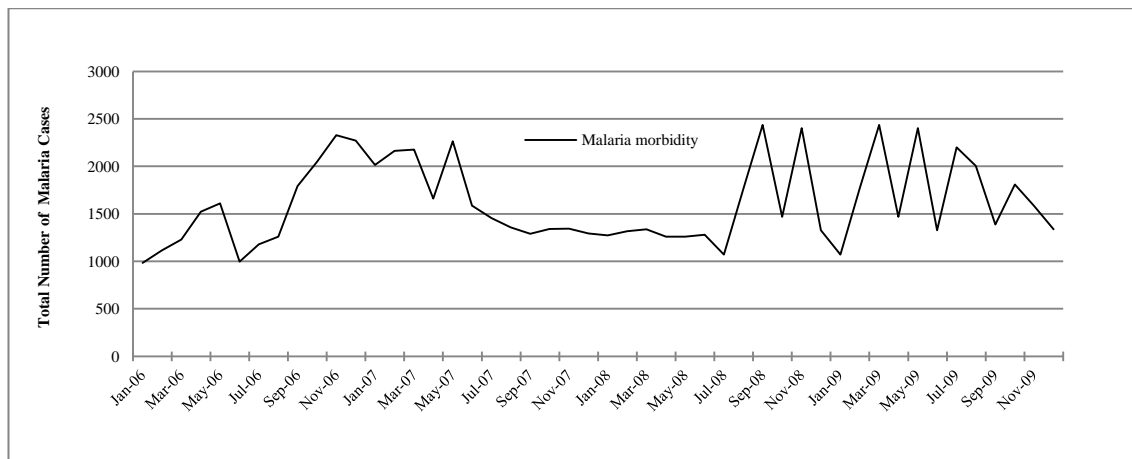


Figure 35: Total number of malaria cases in children less than five years old, 2006–2009

6.2.2 *Distribution of Reporting Health Care Facilities in Lagos State*

In this section, I focus here on data from government-owned health care facilities as the only data providers in Lagos state – which is used for local and international public health decision-making – presented in Figure 37. Though private HCFs exist in the state, they do not have data-gathering or reporting capability. The data from government-owned HCFs is reported to local government units and then as gross annual figures for the state, followed by reporting to the national level.

As stated earlier, this research takes this effort further, to the grassroots, to gather and process data from paper format at such a micro level (in and out patients, monthly, yearly, per health care facility) from over 15,000 records into a georeferenced database which has ordinarily not been available to the state. While this database is not in a perfect format owing to quality issues discussed in the previous chapter, its current state provides an opportunity to initiate and explore spatial and temporal patterns in malaria infection which would have been a Herculean task in the past. Thus, according to Figure 35, the government health care facilities have data-gathering and reporting capacity and as such are the only ones utilised in this research.

The Lagos state government initiative has ensured that each of the 25 local government areas in the state has a health care facility such that its residents have immediate and proximal access to affordable government rated treatment. As this has been a long-term working plan for the state government, health care facilities have been established at

different dates, and as such do not all possess the same temporal range of malaria data.³⁷ While some of the HCFs boast of data dating as far back as 2000, some more recent HCFs have data starting from 2008, and as described earlier, they are often characterised by missing data, as will be made evident as a shortcoming of the data in the subsequent analysis.

6.2.3 Temporal Patterns of Clinical Malaria Infection by Local Government Area

This section is concerned with presenting and discussing annual malaria infection cases reported by local government areas in Lagos state. As noted previously, malaria infection data is generated and reported by HCFs and often collated by local government areas. In this case, malaria data from 25 HCFs have been collated yearly by LGA to assess elevated infection rates across these LGAs. As this study covers a ten-year period (2000–2009), I utilise HCFs with reporting capability that offer data spanning the period.

Figure 38 shows annual totals of malaria cases in 14 LGAs over the period 2000–2009. Across the years, Lagos Island LGA persistently tops the other LGAs in the number of malaria infection cases reported. It recorded its highest level of about 55,000 cases in 2007 and its lowest of about 33,000 in 2002. This is followed by Ikeja LGA, having 22,000 and 35,000 cases in 2003 and 2009 respectively. These are highlighted in red in Figure 36. Other notable LGAs which report elevated infection rates are Oshodi-Isolo LGA, Mainland LGA, Ikorodu LGA, Agege LGA and Kosofe LGAs. Other than Ikorodu and Agege LGAs, on the peri-urban outskirts of Lagos, they are situated in the centre of Lagos.

Alimosho, Apapa and Mushin LGAs report the lowest records of malaria infections across the LGAs. In Alimosho LGA, for example, the number of malaria cases reported was as low as 1,500 in 2004 and as high as 9,800 in 2009 which is equivalent to the lowest records reported in some LGAs such as Kosofe.

³⁷ There are about five newly created local government areas that at the time of data gathering did not have any government HCF and as such will not form part of this analysis.

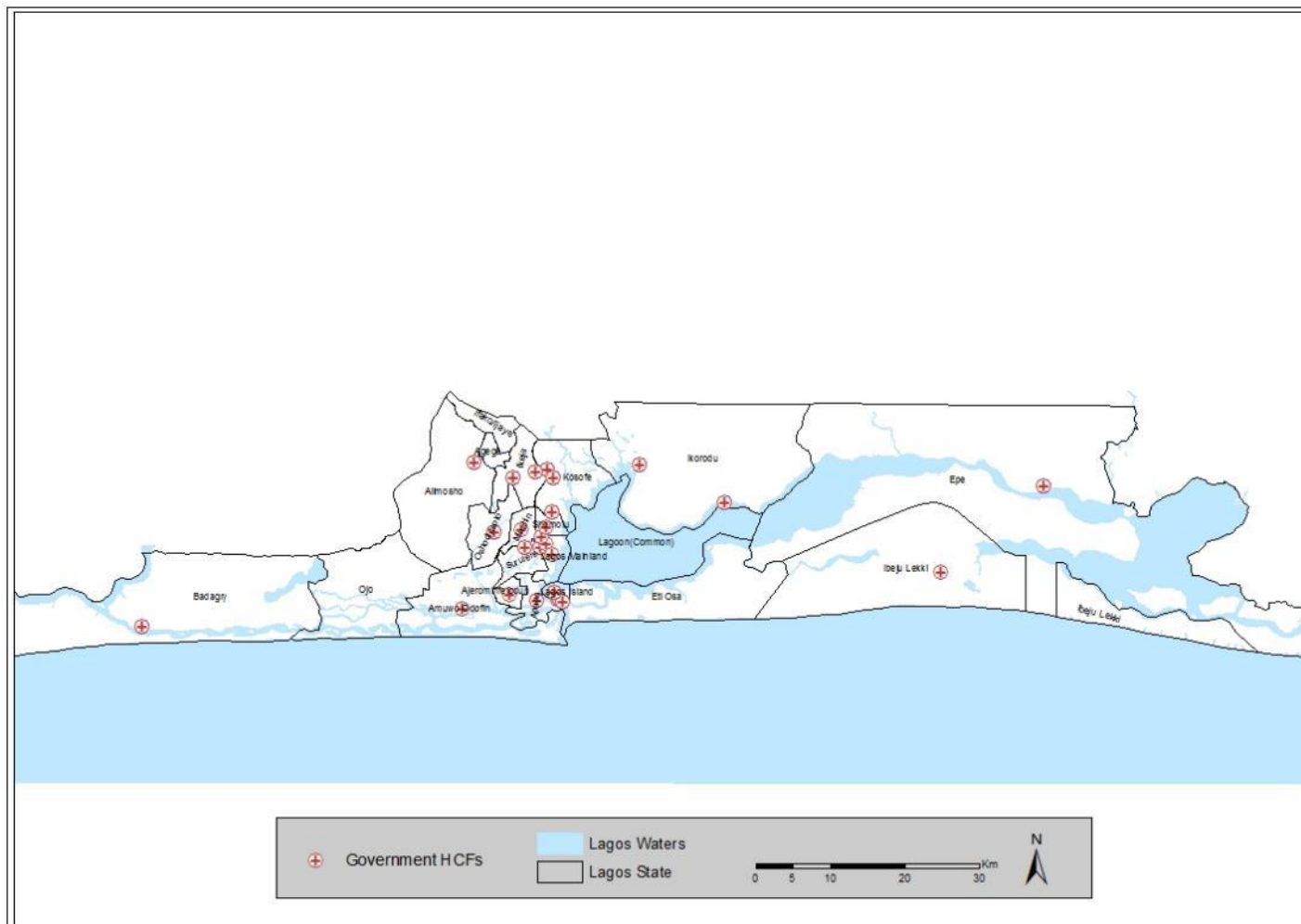


Figure 36: Distribution of LSMoH data-reporting health care facilities by LGA in Lagos state

While I note the LGAs with elevated malaria cases over the period 2000–2009, what I do not know are the HCFs contributing to these LGA figures, the geographic locations of the reporting HCFs, or if these HCFs/LGAs report these rates in one month only, or persistently across the months, such that this contributes to stable endemic malaria conditions. The data that was previously aggregated at LGA level in this section will be utilised from the point of reporting, i.e. the HCF where the data gathering and reporting originates. All available data for at least five consecutive months from all HCFs form part of the analysis.

6.2.4 Exploration and Visualisation of Space-Time Patterns of Malaria Infection

This section focuses on 3D space-time visualisation of monthly HCF malaria infection data and the selection of optimum study locations for in-depth studies using GeoTIME software. There are 25 participating secondary and tertiary HCFs as shown in Figure 39. The HCFs have data available for at least five consecutive months, irrespective of the sequence of months it occurs such that I can identify LGAs with stable malaria situation. Figures 40 and 41 show malaria infection in Lagos state within a spatio-temporal context where figure 40 is the calendar view in months while figure 41 shows the spatial distribution with a coarser temporal axis using annual figures. Both figures reveal that HCFs reporting the highest rates are concentrated within the central business district (CBD) (see HCFs in circle).

The HCF in Amuwo Odofin (Figures 40 and 41) has a concentration of malaria cases in 2001 and between 2002 and 2003. Between 2003 and 2009 there existed periods of underreporting/missing data and this quality issue has been raised in the previous chapter as characteristic of this data. A similar issue occurred with the malaria data from other HCFs but they are of a lesser extent than this HCF. One of the HCFs in the CBD report malaria data from 2000 to 2005 after which there is no data available due to quality issues. During the period of 2000 to 2009, a number of malaria intervention programs were rolled out and the population generally benefited from it. Its impact is revealed in some of the malaria infection rates reported at the HCF. For example at the HCF in Epe there was reduced number of cases between 2000 and 2005. After 2005 number of malaria cases increased and increment in cases may be politically oriented due to change in government that brought about changes in intervention programs that took time to assimilate this impact is also experienced as shown earlier in figure 35.

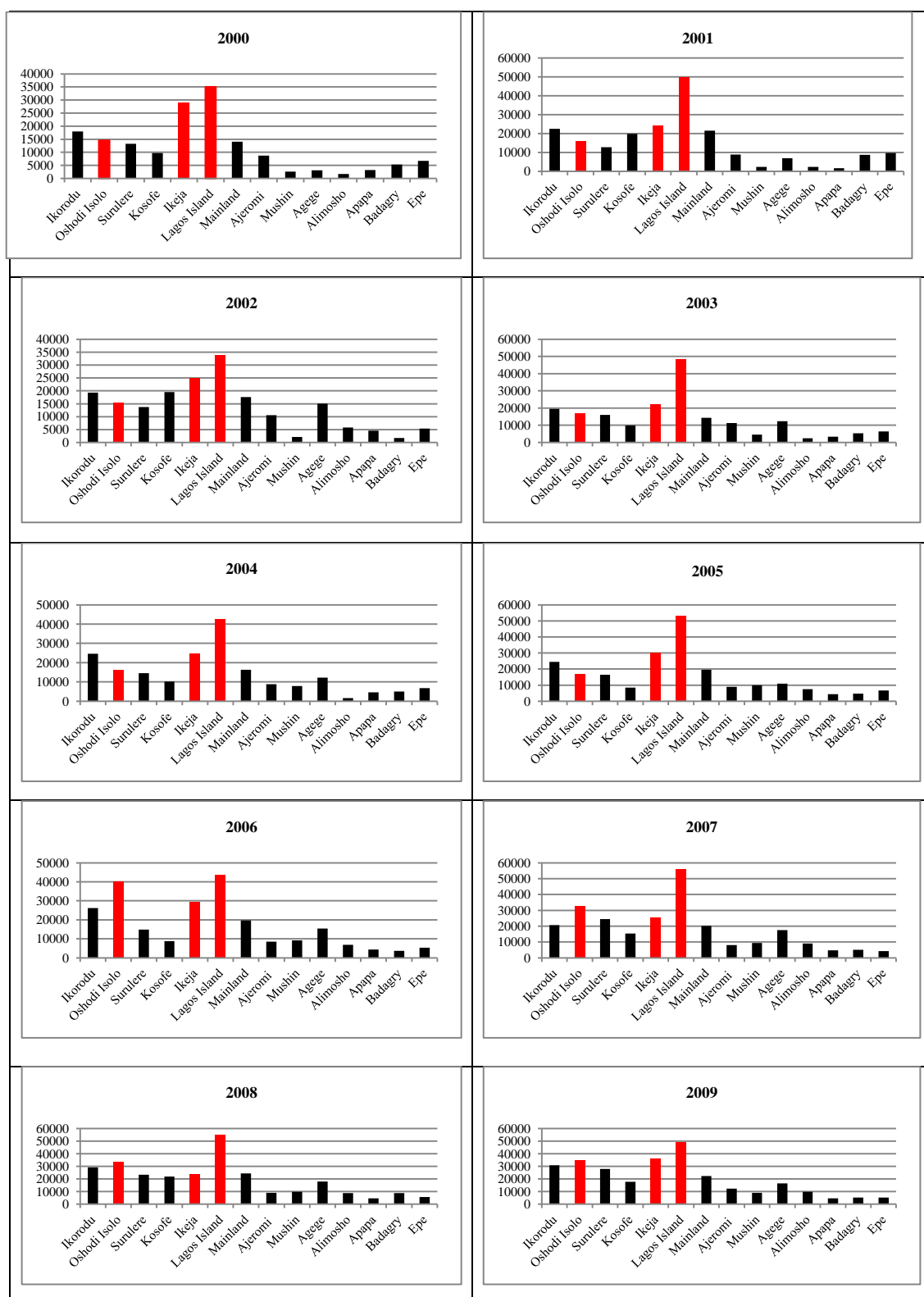


Figure 37: Exploration of temporal patterns of malaria reported by LGAs in Lagos state

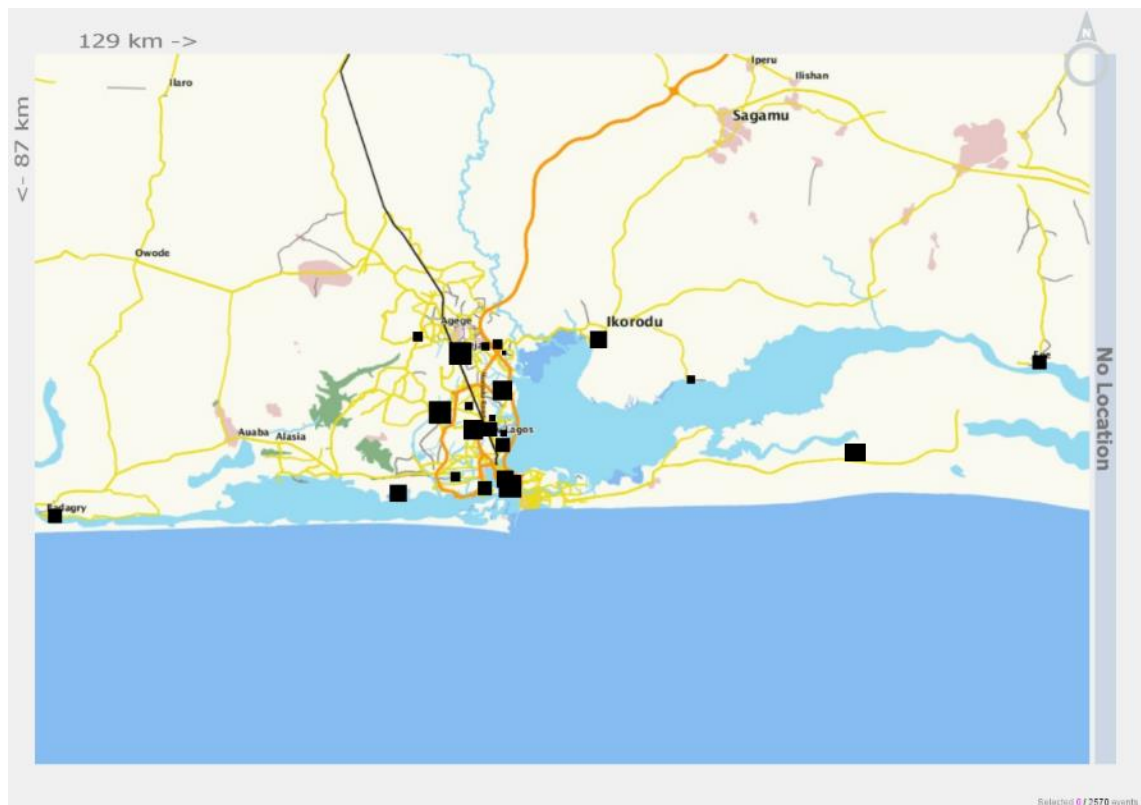


Figure 38: Spatial location of HCFs explored in the identification of elevated malaria infection rates in Lagos state³⁸

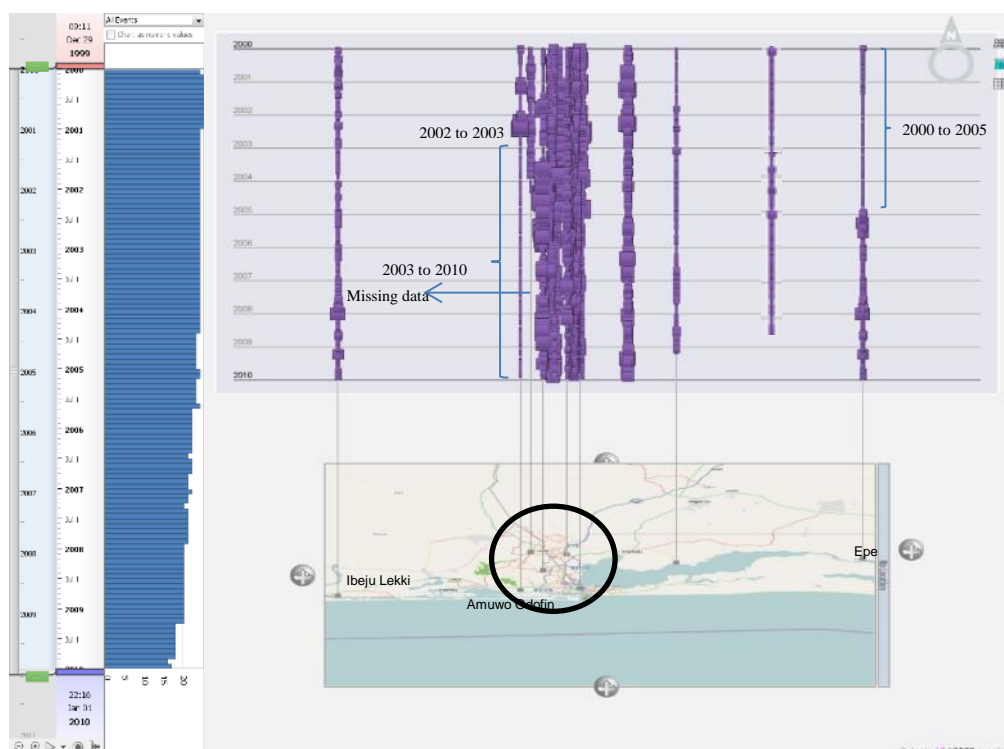


Figure 39: Spatial and monthly temporal characteristics HCFs explored in the identification of elevated malaria infection rates in Lagos state

³⁸ The size of the symbologies in figures 39, 42, 44, 46 and 48 do not represent the incidence of malaria reported by that HCF, but is a 2D view of the level of disease incidence by month as shown in their 3D views in figures 40, 41, 43, 45 and 47. This visualisation is sufficient for the purpose behind this illustration. .

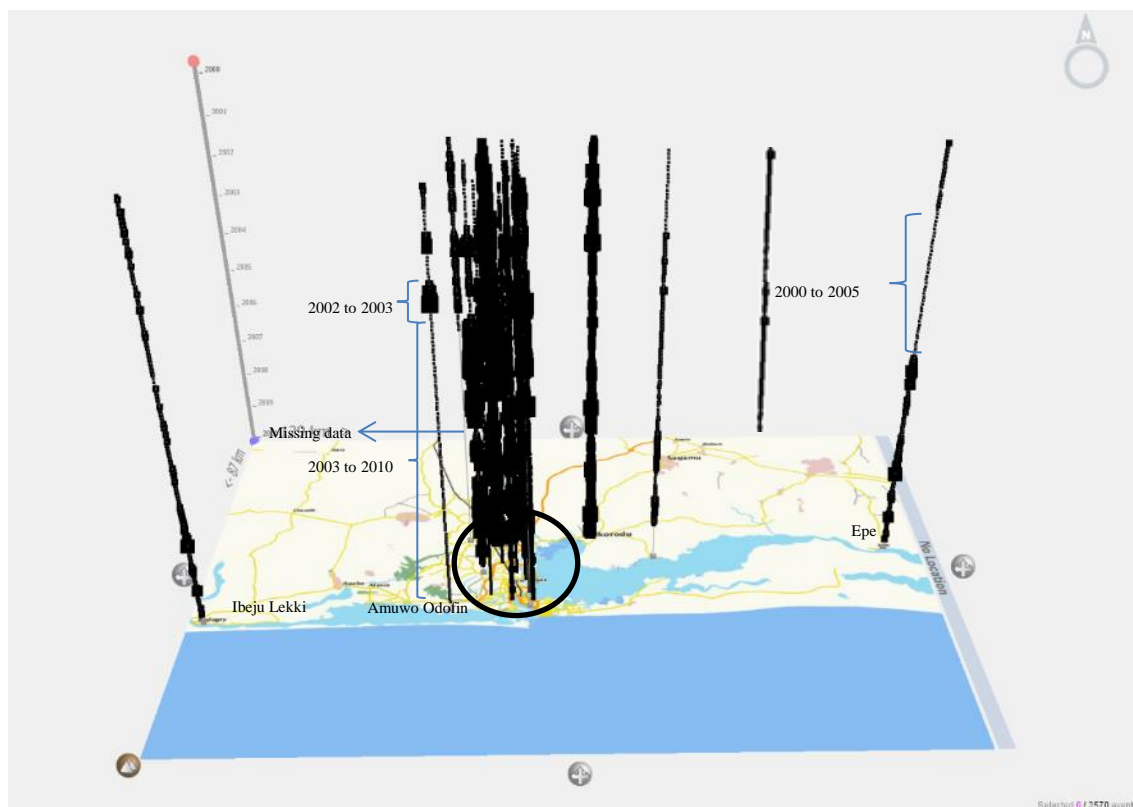


Figure 40: Spatial and yearly temporal characteristics of HCFs explored in the identification of elevated malaria infection rates in Lagos state

To explore the elevated malaria infection status for each LGA, I utilised three incidence rates as stated in the methodology chapter: the median standardised rate (42 per 1000); the average rate (71 per 1000); and the upper quartile rate (180 per 1000) that occur in any five consecutive block of months during the period 2000–2009. LGAs where malaria rates as high as 180 per 1000 and above in its HCFs were further considered for the in-depth study.

Figures 42 and 43 show locations of HCFs that report 42 per 1000 cases and above of malaria infection. From the figures, I note that the 17 HCFs located in 12 LGAs (Mushin, Oshodi-Isolo, Shomolu, Lagos Mainland, Surulere, Amuwo-Odofin, Ajeromi-Ifelodun, Apapa, Lagos Island, Ikeja, Alimosho and Kosofe LGAs) exhibit these rates, with HCFs in LGAs such as Ikeja, Lagos Island, Oshodi-Isolo and Lagos Mainland having rates above 42 per 1000 persons.

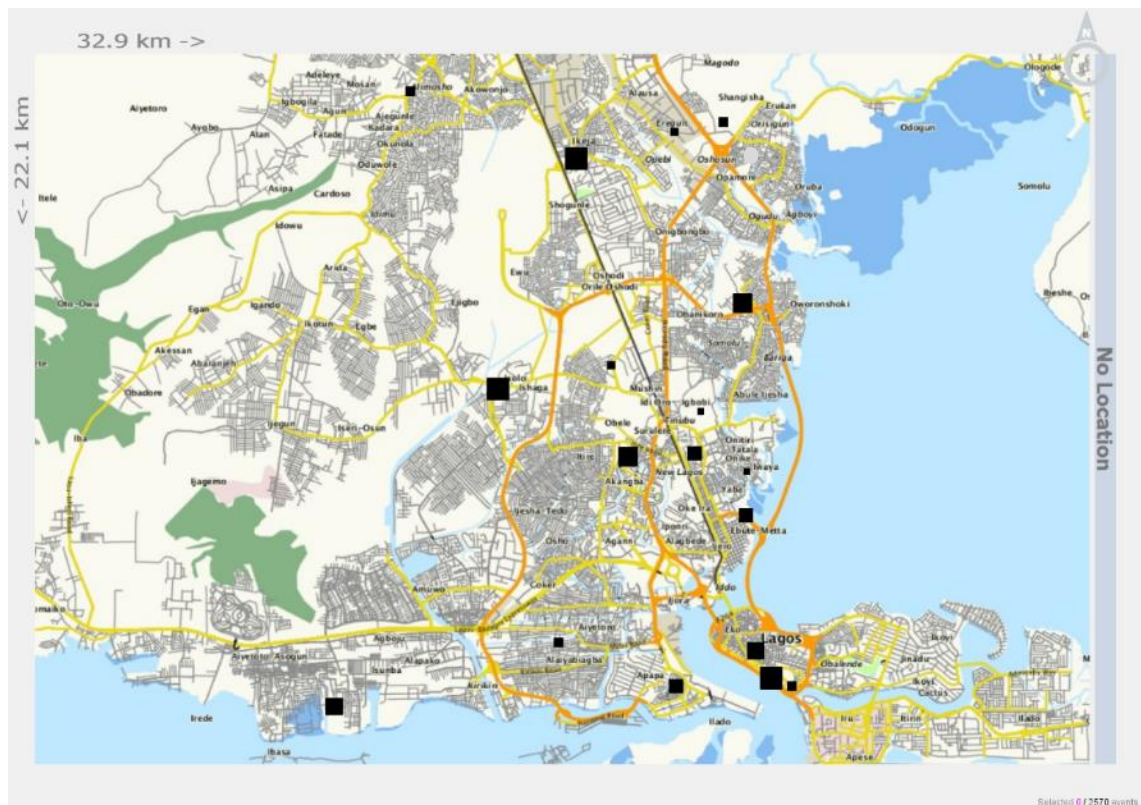


Figure 41: Spatial locations of HCFs reporting malaria infection rate of at least 42 cases per 1000 persons over five consecutive months

As shown in Figure 43, HCFs highlighted in blue report much higher rates above 42 per 1000 throughout the period 2000–2009. Since they are still so many to choose the most suitable location for further study from, I applied the criteria to explore HCFs that report rates above 71 per 1000.

Figure 44 shows the spatial location of HCFs reporting malaria infection rate of 71 per 1000 and above in Lagos. As shown, there are 15 HCFs distributed in ten LGAs (Ikeja, Kosofe, Alimosho, Oshodi-Isolo, Surulere, Lagos Mainland, Ajeromi-Ifelodun, Amuwo-Odofin, Apapa and Lagos Island). The location and the temporal characteristics of infection rates emanating from the HCFs are shown in Figure 45. According to the figure, I still have ten LGAs to select from, but I note that HCFs highlighted in green report rates in excess of 71 per 1000. I then employ the upper quartile malaria infection rate of 180 per 1000 and identify locations of HCFs and LGAs of interest in excess of the average rate. The in-depth study will be situated in one of the resulting locations.

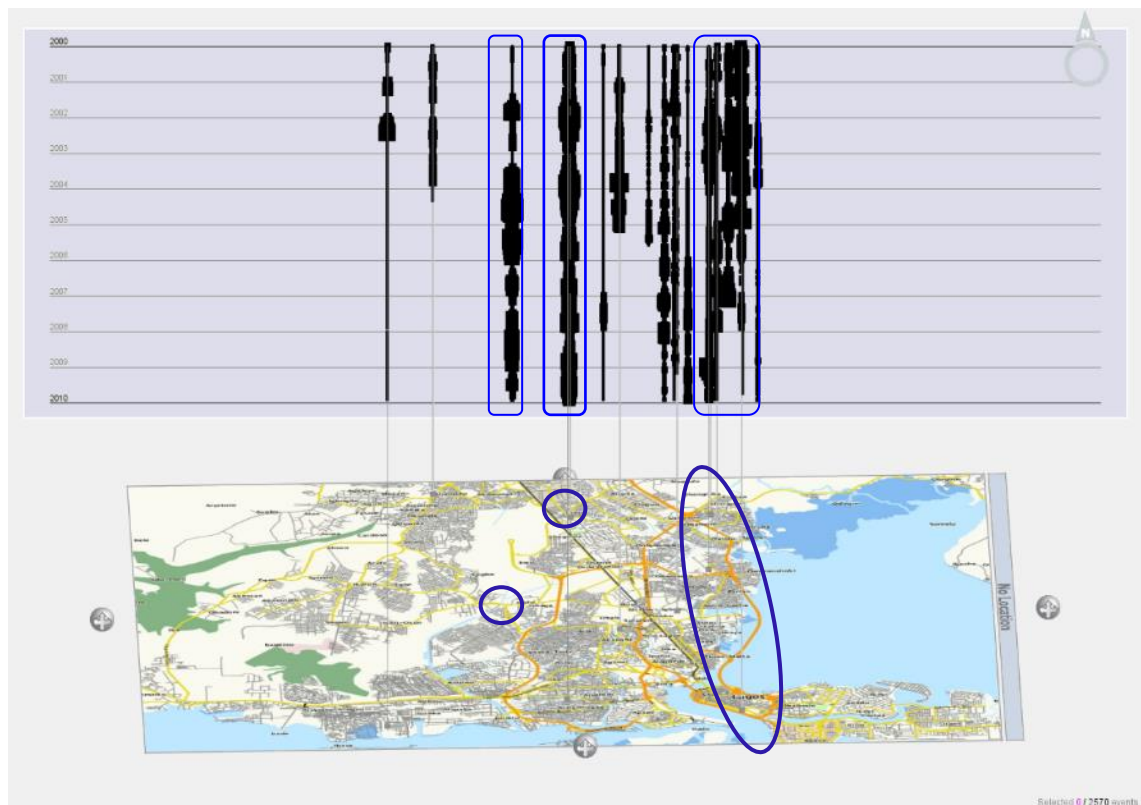


Figure 42: Spatial and temporal patterns of HCFs reporting malaria infection rate of at least 42 cases per 1000 persons over five consecutive months

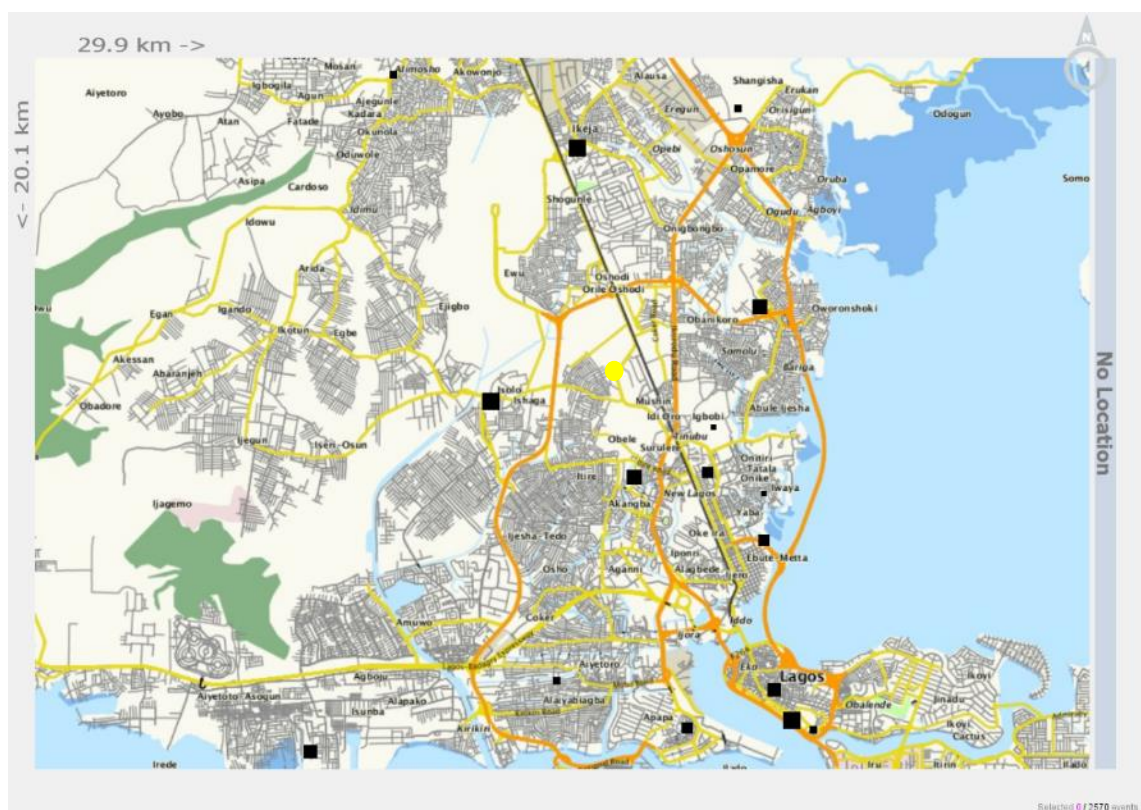


Figure 43: Spatial locations of HCFs reporting malaria infection rate of at least 71 cases per 1000 in five consecutive months



Figure 44: Spatial and temporal locations of selected HCFs reporting malaria infection rate of above 71 cases per 1000 in five consecutive months

Figure 46 shows locations of HCFs reporting incidence rates of 180 per 1000 over five consecutive months within the timeframe of interest. Nine HCFs are of interest and fall within Ikeja, Kosofe, Oshodi-Isolo, Lagos Mainland, Lagos Island, Surulere and Apapa LGAs. In Figure 47 I explore both spatial and temporal reporting patterns for malaria, what is revealed is that the HCFs in these locations have consistently reported high malaria infection rates above 180 per 1000 for at least five months all through the reporting period. These locations are scrutinised further to identify an appropriate location of interest for further analysis.

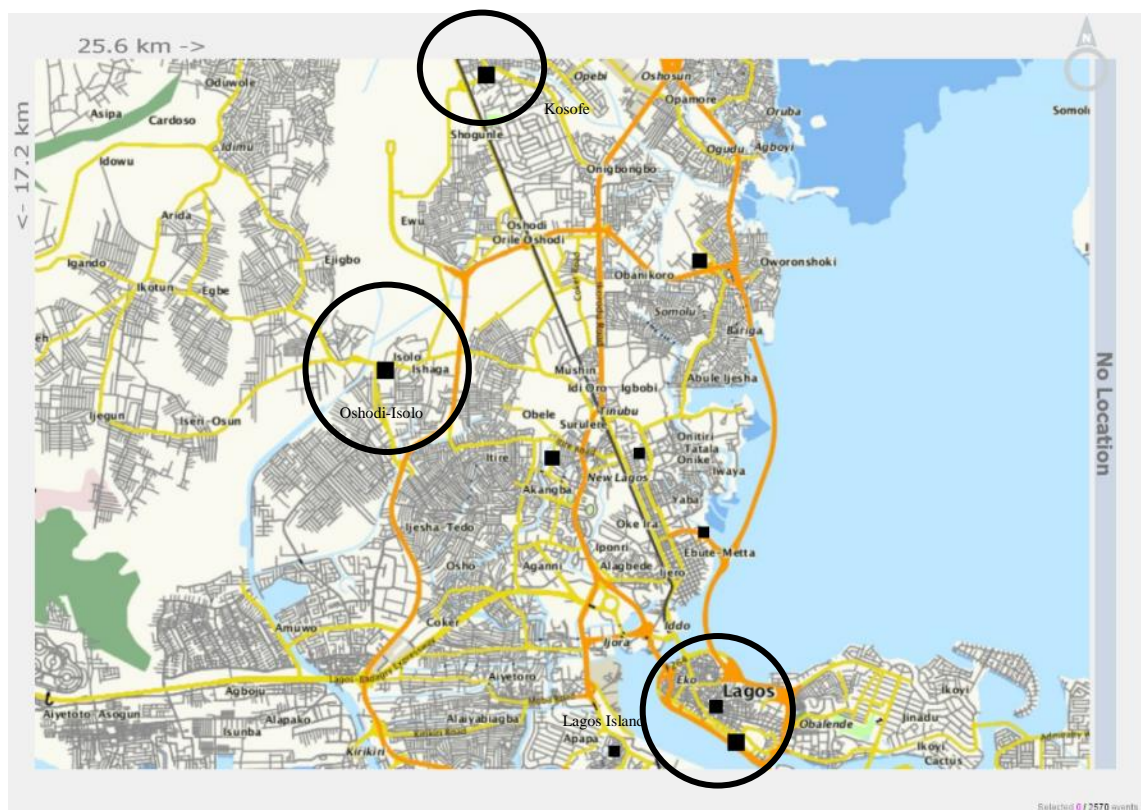


Figure 45: Spatial locations of HCFs reporting malaria rates of at least 180 per 1000 over five consecutive months

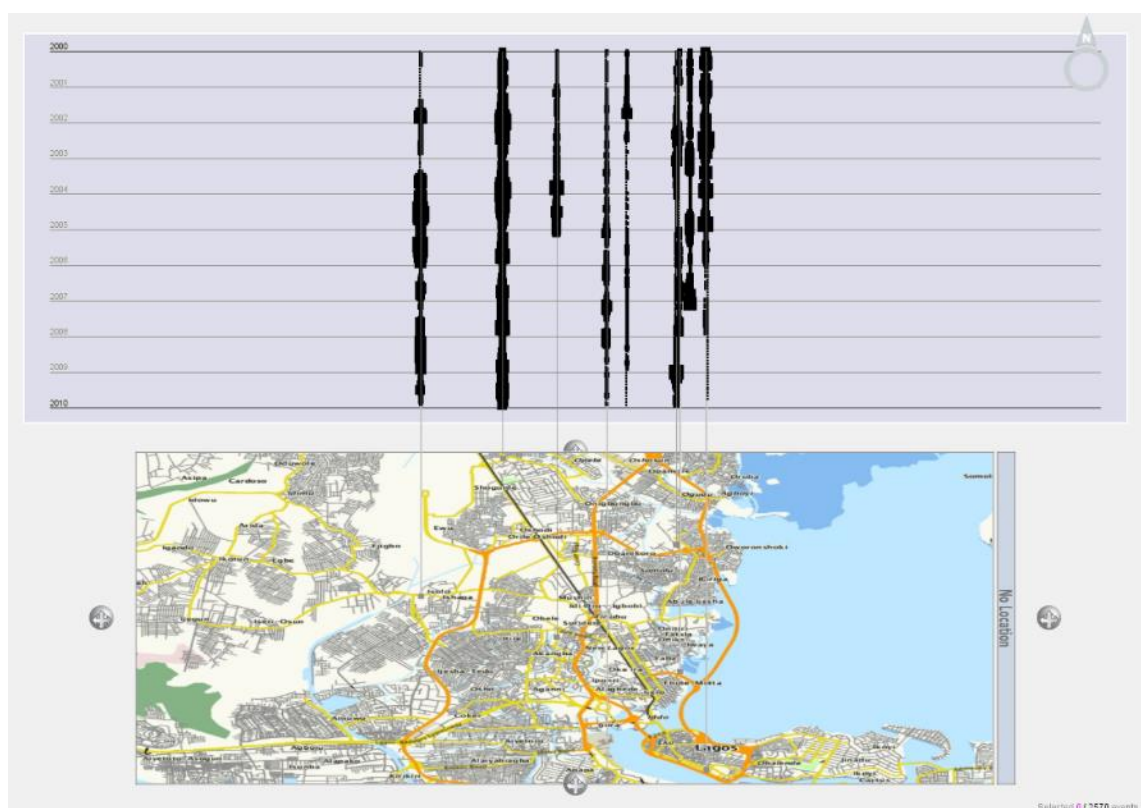


Figure 46: Spatial and temporal characteristics of HCFs reporting malaria rates of at least 180 per 1000 over five consecutive months

While the intention of the Lagos state government is to ensure that HCFs are within immediate reach of the residents, residents do not always exploit services in this way as shown in the infection rates reported by the HCFs in Lagos Island LGA. Lagos Island has a population of about 209,437, yet has had the highest reported level of malaria cases and infection rates, up to as high as 55,000/year and 180 cases per 1000 persons, respectively. Alimosho LGA, with a population of about 1.28 million, has HCFs reporting as low as about 1,400 cases for 2004 and 10,000 cases at its highest in 2007 and 2009, and 71 cases per 1000 persons infection rate. Ikeja LGA has a population of 313,196 persons and report rates as high as 180 cases per 1000 persons and up to 35,000 cases in 2009. Oshodi-Isolo LGA has a population of 629,509 and report annual cases of up to 40,000 in some years, but as low as 15,000 in 2001 and an infection rate of over 180 cases per 1000 persons.

Though the number of malaria cases has been standardised, some unexpected patterns still emerge in areas like Lagos Island, which has the lowest population size amongst the LGAs with the highest elevated infection rate. Lagos Island LGA demonstrates high rates for a number of reasons. Firstly, it is situated in the central business district (CBD) where the majority of businesses and workplaces are located. Patients who work in the CBD are likely to use the HCFs there, due to their proximity to their places of work. Secondly, there are two major specialist hospitals in the LGA: the Massey Children's hospital and the Lagos Island Maternity hospital. These are specialist hospitals for the populations most vulnerable to malaria and thus attract many of the vulnerable patient group all around Lagos state to use them. This means it is likely that of the volume of malaria recorded in the HCFs in Lagos Island likely originate from outside the LGA. Oshodi-Isolo LGA, with high malaria incidence rate, has similar commercial and ecological characteristics to Lagos Island. These LGAs have been eliminated from further consideration for in-depth studies.

Ikeja LGA has the second highest rate of disease and annual total across the study period. Ikeja contains a CBD and a residential area and is the state capital. It is also ecologically and economically diverse, home to a variety of ethnicities which Lagos Island or Oshodi-Isolo LGAs cannot boast of. The LGA is situated in the core of the urban centre of Lagos and its inhabitants have benefited from a range of malaria interventions. It has a meteorological station with more reliable data that covers the LGA and beyond, making it a suitable location for study. Also (Okwa, 2003) study of 6

LGAs reports Ikeja LGA to have the highest rate of infection and Lagos Island with the lowest.

Kosofe LGA, another focal point of interest, has HCFs reporting an infection rate over 180 cases per 1000 persons and over the study period it has reported between 10,000 and 20,000 cases of malaria per annum. The area is residential with some farming and market centres. It has a population of 665,393 persons and is home to a diversity of ethnic communities including the indigenous Aworis and Ilajes. With its population size and malaria reporting rate, there are indications that these cases have arisen from within it. The location is also contiguous to Ikeja LGA and falls under the same meteorological network of the Ikeja station. It has also benefited from many vector control initiatives. This makes it another choice location for in-depth studies.

Ikorodu LGA, which is also characterised by a number of cases as high as 30,000, and LGAs like Epe and Badagry with less than 10,000 are excluded from this exploratory analysis because their locations are classified as peri-urban.

Even though the malaria data does not depict outbreak at place of infection and is characterised by missing values, I have adopted an approach that uses the data characteristics with the flexibility of the density approach to overcome these limitations. In doing this I have identified LGAs which have elevated incidence levels. The GeoTIME cluster-finding algorithm is unique in the sense that its single snapshot approach and use of symbolisation to represent intensity of disease incidence spatio-temporally presents the uniqueness of this method, which traditional GIS cannot perform easily. Its weakness, though, is that its results are not statistically confirmed, which can raise some criticism, and preference for other methods like the spatial scan statistics. Its ability to represent intensity using symbolisations that are visually discernable still makes it relevant and appropriate for the exploratory task I have undertaken. The selection of Ikeja and Kosofe LGAs in collaboration with other ecological factors for further study once more confirms the pertinence of human judgement.

In the next section, I progress to the first aspect of the in-depth study to examine the relation between malaria infection and meteorological variables in a time-lagged correlation analysis in the selected LGAs of Ikeja and Kosofe.

6.3 The Impact of Meteorological Factors on Malaria in Ikeja & Kosofe LGAs

In this section, I build on Oluleye and Akinbobola's (2010) study in Lagos to examine additional meteorological variables of temperature and rainfall at monthly temporal resolutions and in a micro-location. In so doing I identify variables that are most significantly associated with malaria infection under time-lagged conditions that take into account the time required for the climate to impact on vector and parasite bionomics. While I aimed to address this relationship at a broader spatial scale to understand how these impacts relate to malaria infection in Lagos state, owing to local variations in climate that interact differently with malaria (Nath and Mwchahary, 2013) and data availability considerations, I address scale issues by focusing on Ikeja and Kosofe LGAs, which have more complete and reliable data on malaria infection and climate over the period 2000–2009.

6.3.1 Descriptive Analysis of Malaria Infection and Meteorological Variables

I start by first understanding the characteristics of malaria infection data and meteorological variables such as monthly total rainfall, mean temperature, relative humidity, number of rain days and sunshine duration.

6.3.1.1 Malaria Infection Data

According to Table 7, across the ten-year study timeframe, monthly total malaria cases in Ikeja and Kosofe LGAs ranged from 90 to 3749 cases, occurring in the months of January 2002 and April 2008 respectively, as also shown in Figure 47. The total number of malaria cases for the period is 129,392 with an average of 1,078 malaria cases occurring per month. The standard deviation of the number of malaria cases ($\sigma = 584.34$) shows how dispersed the reported figures are from the average number, an indication of high variability in the number of cases reported across months and even years, as also shown in Figure 49.

Table 7: Summary of monthly malaria infection in Ikeja and Kosofe LGAs

<i>Variables</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Std. Deviation</i>	<i>Total</i>
Number of Malaria Cases	90	3,749	1,078	584.34	129,392

From Figure 49, the pattern of monthly malaria cases is such that it is multimodal (across 2000 to 2009) with distinct peaks in May 2002 and 2008. Across these years, the magnitude of cases varied at different times in the year. For example, in 2001, just over 2,000 cases of malaria occurred in August and October, with a similar pattern in 2009. August is the short dry season (August break) after the long wet season (April to

July). In 2002, distinct peaks between 2,000 and 2,500 cases occurred in March and May, just as in 2003, but in a lesser magnitude. In 2003, there was a sharp decrease in the number of malaria cases owing to a significant strike action by health workers. A cyclical pattern continued between January and June 2003 and decreases from June 2003, remaining almost steady until January 2007 when it increased slightly throughout the year with a small fall in April and July of the same year until February 2008. From the middle of 2003 to the end of 2006, the number of cases per month levelled off at about 500, rising to about 1,000 throughout 2007. While there were often local maxima across the period, they occurred irregularly and at different magnitudes and times. In 2008 two peaks occurred in April and June and one peak occurred in August 2009.

6.3.1.2 Meteorological Variables

According to Table 8 and Figures 50 to 54, average relative humidity ranged from 49% to 86%, and the minimum level occurred in February 2000 with the highest in June 2007. Some months such as January 2005 and 2007, February 2007 and 2008, and December 2003, 2004 and 2009 went without rainfall, corresponding to months without rain days, while in June 2009 the highest rainfall of 463.4mm occurred in 16 days. These correspond to the peaks of the dry and wet seasons respectively. The highest number of rain days (22) occurred in two months, one with only 69.5mm of rainfall and another with 442.7mm of rainfall in the months of June 2003 and July 2008 respectively. The amount of rainfall averaged 127.7 mm ($\sigma = 117.62$), indicating a large variability, often cyclical from season to season as shown in Figure 51, while the average number of rain days is 8.48 ($\sigma = 5.86$) showing a minimal variation across the same period even though the rainfall amount varied considerably more.

Table 8: Summary of monthly meteorological variables in Ikeja and Kosofe LGAs

<i>Variables</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Std. Deviation</i>	<i>Total</i>
Total Rainfall (mm)	0	463.40	127.47	117.62	15,296.53
No. of Rain Days	0	22.00	8.48	5.86	1017
Average Relative Humidity (%)	49	86	75.77	7.12	
Number of Sunshine Hours (hours)	1.43	436.13	35.45	77.17	2,127.2
Mean Temperature (°C)	25.35	30.75	27.78	1.37	
Minimum Temperature (°C)*	22.60	26.70	24.06	0.95	
Maximum Temperature (°C)*	27.70	38.60	31.56	2.16	

*Data on these are incomplete so not used for any further analysis

The monthly minimum and maximum mean temperature ranged from 25.35 to 30.75°C, with maximum temperatures often occurring in the months of March and April at the cusp of the long dry and wet seasons. Maximum temperatures ranged between 27.7°C and 38.6°C, with minimum temperatures between 22.6°C and 26.7°C. The minimum

and maximum number of sunshine hours occurred in the months of August and June, corresponding to the August dry break and wet season, respectively. The average monthly maximum temperature was 31.56°C ($\sigma = 2.16$) showing minimal variation compared to the average number of sunshine hours, which was 35.45 ($\sigma = 77.17$) and which had wide variability.

6.3.2 Malaria–Meteorological Variables Relationships

I qualitatively examined the relationship between malaria and multiple climatic variables using graphs that show the monthly magnitude of cases for each month of the period being studied. The study area is also characterised by four seasons and this is demarcated in the graph for easier visual appreciation and also often reflected in the patterns of the meteorological variables but not the malaria infection trends.

Figures 50 to 54 show that the magnitude of malaria cases did not always follow the characteristics of the meteorological variables. For relative humidity (Figure 50) at periods where the values were relatively steady, as in June to December 2003 and 2005, the number of malaria cases had the same pattern. I note however that in August (see Figure 51) when the short dry season occurs and the rainfall amount is lower than other months (2000, 2001, 2007 and 2009) the number of malaria cases peaks. Other peaks have been at the start of the rainy season (April 2000: second month of the rainy season; October 2001, May 2002, May 2003: short wet season) while others have occurred in the long dry season (November 2000, March 2002, December 2009). There are no particularly distinctive seasonal patterns, as malaria occurred in magnitudes of at least 90 cases irrespective of season. It has occurred and peaked even when rainfall is less than 100mm or even zero (for e.g, January 2007 and December 2009).

For mean temperature, cases of malaria infection have occurred when they are at a minimum of 26°C, up to almost 32°C (Figure 52). At these temperatures, transmission is possible, sustainable and stable across seasons. Peaks have occurred at temperatures of about 25°C to 30°C which mainly characterise the wet season. At maximum temperatures of 38.6°C, which is above that favourable for anopheles survival, malaria transmission continues.

The pattern of relationship between malaria and rain days is no different from rainfall amount (Figure 53). None of the peaks have occurred in the months with the highest number of rain days. They have always occurred in the months of reduced numbers of rain days, for example in August, as found similarly with rainfall amount.

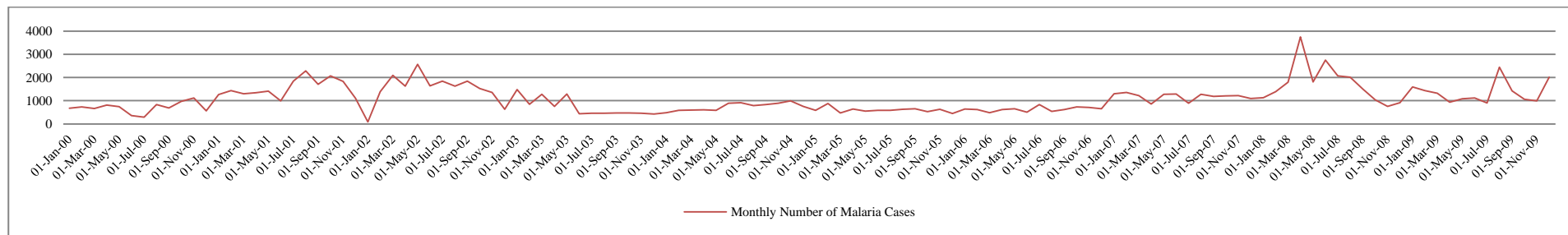


Figure 48: Monthly totals of malaria cases in Ikeja and Kosofe LGAs, 2000–2009

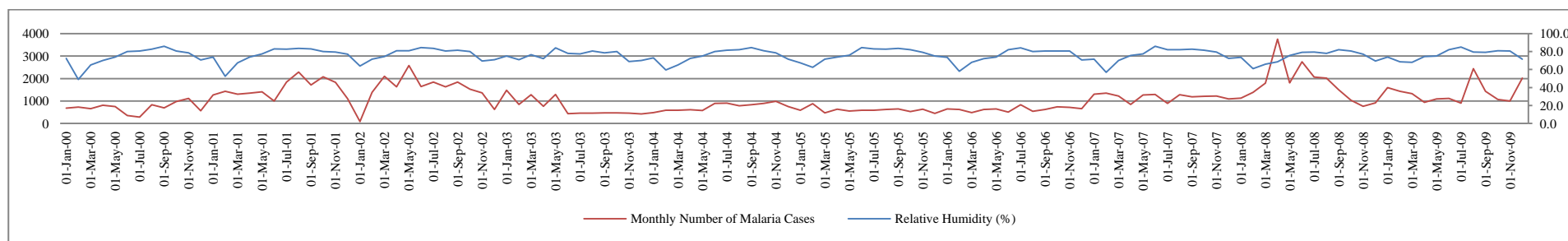


Figure 49: Monthly average relative humidity and malaria infection, 2000–2009

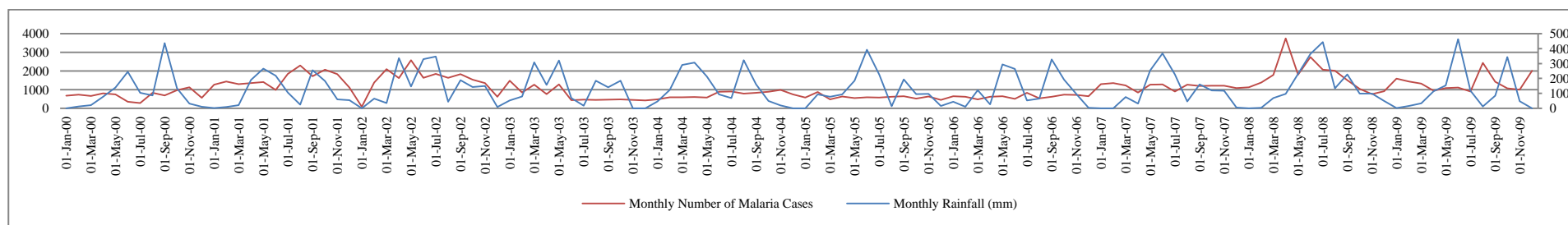


Figure 50: Monthly total rainfall and malaria infection, 2000–2009

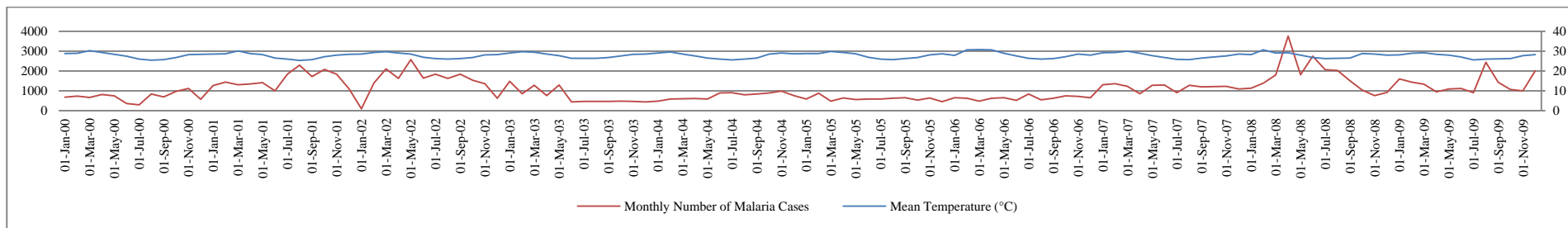


Figure 51: Monthly mean temperature and malaria infection, 2000–2009

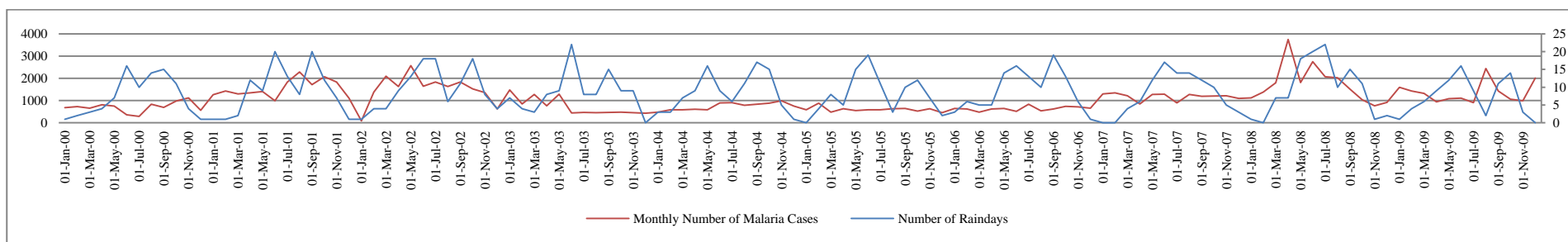


Figure 52: Monthly number of rain days and malaria infection, 2000–2009

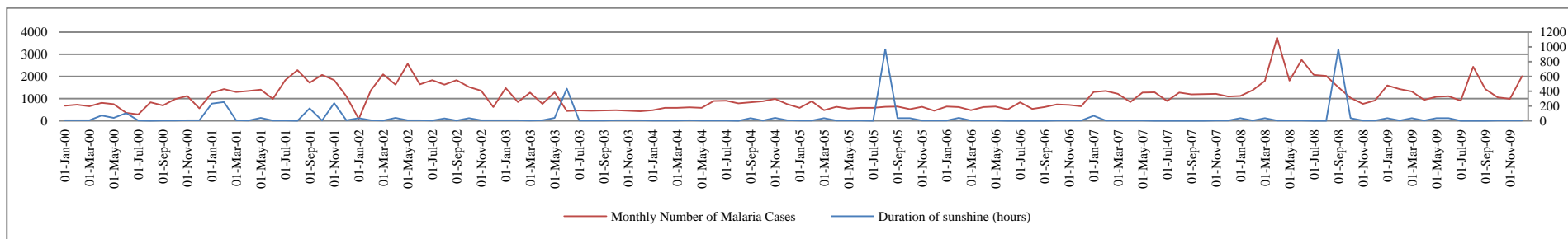


Figure 53: Monthly sunshine duration and malaria infection, 2000–2009

With respect to sunshine duration (figure 54), a reduced number of malaria cases occurred during periods of little or no sunshine in 2003 and 2004. In other years, the pattern is irregular.

In summary, while there are obvious temporal patterns in the meteorological variables, malaria infection has not shown any likelihood of regular patterns closely matching that of the meteorological variables.

6.3.3 Time-lagged Correlation between Malaria and Meteorological Variables

Climatic variability is often cited as an important risk factor contributing to the increasing spread of malaria despite its relationship being more or less an indirect one. I exploit this relation using the monthly totals of clinical malaria cases and the meteorological variables summarised earlier, using a time-lagged correlation analysis in an urban centre situated in the heart of Lagos state.

As shown in Table 9, none of the meteorological variables are significantly associated with malaria at all the biologically plausible time-lags considered. At no (zero) time-lag and the one-month time-lag, the mean monthly temperature is negatively and weakly associated with the number of malaria cases reported. Its non-significant association remains, at increasing time-lags of two and three months, but only changes to become a positive relationship. Other variables such as the number of rain days and hours of sunshine are weakly and positively associated with malaria at no lag up to two months, after which they become negatively and still weakly associated with malaria infection. None of the associations are statistically significant.

Monthly total rainfall amount shows both positive and negative non-statistically significant relationships with the number of clinical malaria cases at the four time-lags, while relative humidity is positively associated with malaria infection in the initial two months, after which it becomes negatively associated with malaria at the two and three months' time-lags.

The pattern of monthly malaria infection shows that at all time-lags, all five meteorological variables in Table 9 have little or no influence on the way it occurs.

Table 9: Time-lagged correlation of monthly malaria and climatic indices in Lagos state

	<i>Mean Temperature (°C)</i>	<i>Number of Rain Days</i>	<i>Sunshine Duration (hours)</i>	<i>Total Rainfall (mm)</i>	<i>RH (%)</i>
no lag	-0.069 (0.455)	0.111 (0.229)	0.041 (0.454)	0.102 (0.269)	0.097 (0.292)
1 month lag	-0.063 (0.519)	0.071 (0.465)	0.011 (0.235)	-0.011 (0.414)	0.014 (0.617)
2 months lag	0.114 (0.269)	0.028 (0.487)	0.016 (0.600)	-0.041 (0.608)	-0.048 (0.641)
3 months lag	0.036 (0.444)	-0.018 (0.369)	-0.148 (0.254)	0.004 (0.571)	-0.017 (0.440)

* Significant at 95% CI, p-value in brackets; RH: Relative humidity

According to Figure 55, the strength of association between the meteorological variables and malaria varied at differing time-lags. At zero time-lag, the number of rain days had the greatest association and decreased gradually until the two-month time-lag, when temperature becomes more related to malaria than other meteorological variables. At the three-month time-lag, the duration of sunshine has the greatest association with malaria.

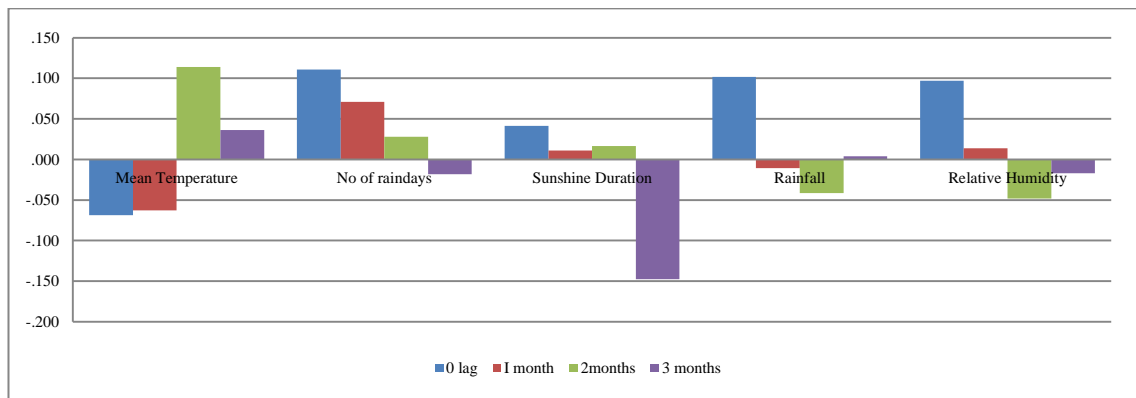


Figure 54: Graph showing correlation coefficient (r) of malaria–meteorological variables relationship at four time-lags

When the p-values of the relationships are explored further (Figure 56), I note that while none of the variables are statistically associated with malaria, some, such as number of rain days at no time-lag, and sunshine duration at the one-month and three- month lags, with p-values less than 0.25, suggest some practical significance in its association with malaria.

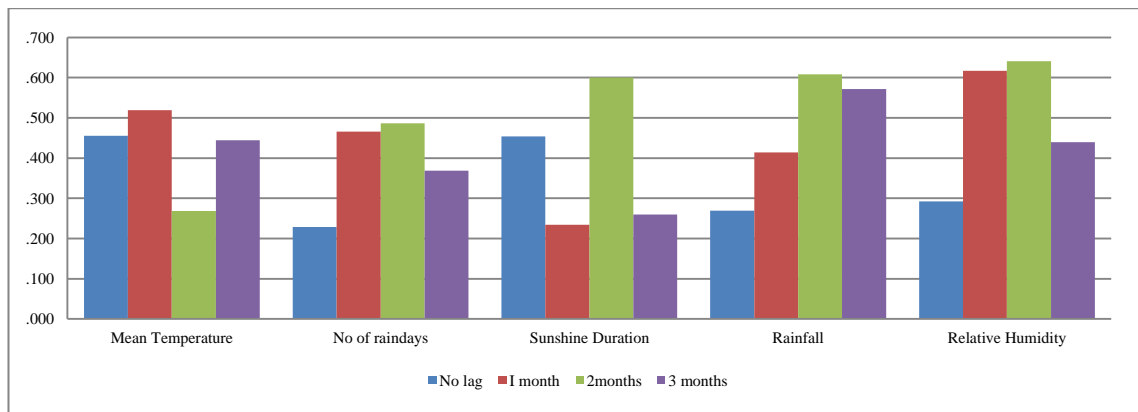


Figure 55: Graph showing distribution of p-values of malaria–meteorological variables relationship at four time-lags

None of these meteorological variables are statistically significant with malaria infection and often move in unexpected directions when compared with evidence from the literature. In the next section, I compare my findings in all analysis in the previous sections with evidence from the literature and discuss their implications.

6.3.4 Discussion

The way weather affects malaria–vector–parasite dynamics varies from place to place and at multiple spatial scales. However, evidence has shown that 90% of the anopheles mosquitoes with the parasite will survive at locations where temperatures are between 16°C and 36°C, with an optimum range between 28°C and 32°C (Craig *et al.*, 1999; Ye *et al.*, 2008), rainfall as low as 2.3mm up to 200mm (Fournet *et al.*, 2010), and relative humidity 60% and above have been confirmed for peri urban and urban areas (Service and Townson, 2002; Ye *et al.*, 2008; Tay *et al.*, 2012). Locations meeting these criteria, such as Ikeja and Kosofe LGAs, should accommodate high vector densities and where significant fluctuations occur over time and space, as is characteristic of climate at small geographic scales, this density will vary by season (Feddema *et al.*, 2005), particularly in urban locations.

Seasonality of mosquito abundance has also been assessed by Awolola *et al.* (2002b) in other parts of Lagos. It has been demonstrated that density of mosquitoes translates to higher human–vector contact and, in turn, higher records of malaria infection (Ye *et al.*, 2008). This is not always the case, as predation is a major influence on survival rates of anopheles such that the vectors do not survive long enough to transmit malaria. Predation includes vector control activities. It could also be that human preventative behaviours and other socio-cultural and environmental factors can inhibit this pre-assumed relationship such that its impact is minimised, thus precluding significant

associations between meteorological variables and malaria, as has been the case in this study (Mouchet *et al.*, 1998; Bi *et al.*, 2003). In this research, none of the five monthly meteorological variables (rainfall, mean temperature, average relative humidity, sunshine duration and number of rain days) portrayed any statistically significant relation with monthly total clinical malaria infection cases at the four time-lags considered.

Some studies have shown insignificant relations between malaria infection and one or more of the meteorological variables, but none has shown a lack of statistically significant association across all variables and time-lags with malaria as this research displays. For example, while it is established that a form of relationship exists between a measure of temperature and malaria infection, in this study, mean monthly temperature has no statistically significant relation with malaria at any time-lags. This finding is inconsistent with Ye *et al.*'s (2008) study on *plasmodium falciparum* infection in peri-urban locations of Burkina Faso, where an increase in mean monthly temperature significantly increased anopheles densities and, in turn, the number of malaria cases at the one-month time-lag, but consistent with Tay *et al.* (2012) study that employs maximum and minimum temperatures and found a non-significant immediate negative association with malaria infection at the zero and one-month time-lags and a positive relation at the two and three-month time-lags. In Akinbobola and Omotosho (2011) study in Lagos, temperature and malaria displayed both positive and negative relationships, which are often weak across the year, apart from the dry season months of February, November and December.

Similarly, with the way rainfall provides appropriate breeding grounds and moisture needed to develop and sustain anopheles habitats, one would expect that such seasonal and high rainfall amounts ranging between 0mm and 463mm in Ikeja and Kosofe LGAs would trigger seasonal densities of vectors with a significant influence on malaria infection in similar directions. However, this is not the case, as the seasonality of rainfall, as shown in Figure 51 and Table 9, is marginally influential on malaria irrespective of its direction of influence. There have been inconsistent reports of such associations from previous studies. The lack of association and marginal influence is consistent with Tay *et al.* (2012) findings in urban communities of Kumasi, Ghana. Similarly, Zhang *et al.* (2010) study in Jinan, China did not find any clear association between monthly malaria cases and rainfall. Akinbobola and Omotosho (2011) study in

Lagos found high negative and positive associations with malaria infection in the dry and wet seasons, respectively, but the study does not report its statistical significances, and focuses on monthly total rainfall gathered averages over 60 years, making it difficult to relate its findings to this study. Ye *et al.* (2008) study found that a cumulative minimum of 100mm of rainfall is required for any effect on vectors and, in turn, malaria. This inconsistency with rainfall and malaria similarly translates to the association between malaria infection and number of rain days. While there is no clear explanation for these differences, local factors and types of rainfall measures employed in the study may have been influential.

Relative humidity is said to be a product of rainfall and temperature, and determines the life span of the anopheles mosquito and thus its ability to transmit the plasmodium parasite to humans (Service and Townson, 2002; Sinden and Gilles, 2002). Its insignificant relationship with malaria at all time-lags, while consistent with some studies like Tay *et al.* (2012) is inconsistent with others such as Ye *et al.* (2008) and Zhang *et al.* (2010), who find relative humidity to have a significantly positive impact on incidence of disease at the time-lags examined. Similarly, the monthly duration of sunshine has failed to have any significant influence on malaria infection and is inconsistent with Li *et al.* (2013) findings of a statistically significant relationship.

Ikeja and Kosofe LGAs, being situated in the centre of urban Lagos, show significantly different relationships between malaria and meteorological variables when compared with most studies. As Tay *et al.* (2012) state, urban centres are associated with a complexity of factors combining with climate to contribute to malaria, and which are yet to be fully understood. This is in agreement with some of the outcomes of the climate–malaria debate that suggests other demographic and social factors working hand in hand to influence malaria patterns. This is also the case in the Ikeja-Kosofe area, as the high incidence of malaria and lack of association with meteorological variables may be associated with the ability of the locality to sustain conditions favourable for vector presence all year round, such that the location is characterised by stable malaria transmission throughout the year.

Craig *et al.* (1999) and Ye *et al.* (2008) demonstrate that at least 80mm of rainfall occurring for at least five months accompanied by a temperature of 22°C and at least 60% relative humidity is required for stable malaria transmission to ensue. Ikeja and Kosofe LGAs are characterised by an average of 127mm of rainfall, and across the

period studied, this has occurred for at least five months, and the minimum temperatures all through the period was 22.6°C. Once a minimum relative humidity of 49% occurred but this is not enough to deter transmission as mosquitoes has been reported to transmit in other parts of Nigeria where temperature is prevailing and relative humidity ranged from 21% up to 84% (Okogun *et al.*, 2005). These climatic conditions are favourable for vector presence and transmission all year round and this is reflected in the volume of malaria infection cases reported throughout the period studied. The average monthly number of malaria cases (1,078) recorded in this study location tower above similar studies such as Zhang *et al.* (2010) in Jinan, China ranging between 10 and 400 cases or Tay *et al.* (2012) in Atonsu, Kumasi, Ghana with an average of only 104 cases, even though these are urban centres. Thus, if the conditions for stable malaria transmission – which means conditions favourable for vector presence – exist all year round, then it is likely that malaria will occur all year round with slight seasonal variability that should be statistically significant or at least reflect an increase or decrease in impact. It is this seasonality that is not evident in this study. However, as Tay *et al.*'s (2012) findings demonstrate, urban areas are complex and often influenced by a myriad of factors that are both climatic and non-climatic; it is often difficult to separate the extent of contribution of these factors, so that climatic influences become blurred. Thus, the ability to separate these will shed more light on the relationship; as summed up from Lafferty (2009) climate–malaria debate that dwelling on only climatic factors without consideration of other social and economic issues can distract the search for a lasting solution to the disease.

6.4 Conclusion

Evidence from preliminary findings showed that Ikeja, Lagos Island and Oshodi-Isolo LGAs are characterised by elevated malaria infection rates over space and time. According to Cromley and McLafferty (2012), scale and population are important factors when examining patterns, and at larger scales, processes creating these elevated rates of disease have less localised causes and are more associated with climate, culture, legislation and politics. In this study, these areas are highly populated, as noted earlier, and high infection rates do not necessarily mean the disease is localised in these LGAs, as areas such as Lagos Island LGA are situated in the largest CBD of Lagos state and thus are often used by patients who prefer to visit HCFs near to their place of work over those closer to their homes. In terms of climate, this may be true as climate variability

occurs across the state. However, this was not explored in this study but rather focused on the influence of the microclimate of Ikeja and Kosofe LGAs on malaria infection.

According to Feddema *et al.* (2005), at smaller geographies, anthropogenic changes create microclimate conditions that differ from globally recorded ones and the way they impact on disease patterns. In Ikeja and Kosofe LGAs, the way meteorological variables influence monthly malaria infection at differing time-lags are inconsistent with many documented relationships in urban locations where similar studies have been conducted. These findings are, though, similar to Tay *et al.*'s (2012) results, but are limited in the temporal resolution of the data utilised and the examination only of indirect relationships, unlike Ye *et al.*'s (2008) study that examined both malaria and vector densities. The lack of malaria infection data and clinical malaria infection data on a weekly or daily basis to allow us to capture important aspects of the vector and parasite development and reproduction stage, which occurs nine to ten days after an infectious bite, however, limits us from drawing full conclusions about this relationship.

In the next chapter, I will further examine Ikeja and Kosofe LGAs by conducting an in-depth study of malaria in households, considering both climatic and non-climatic factors associated with the human ecology of disease which is suggested to contribute to the complexity of the disease in urban centres.

Chapter Seven: Environmental and Socio-Cultural Risks to Malaria

7.1 Introduction

This chapter is a response to research objective four: to investigate the urban malaria transmission risks in relation to environmental and behavioural (socio-cultural) exposures in households living in Ikeja and Kosofe LGAs. It will build on the earlier research presented in Chapter Six to additionally examine the influence of non-climatic variables on urban malaria in a sample of households through the development and evaluation of candidate predictive models within the context of a human ecology of disease framework. By utilising human voices as a backdrop I give meaning to the interpretation of quantitative relationships and through it, contribute to knowledge in the testing and application of theory.

As a first step, I assess the quality of the household survey data that will be utilised to undertake this research and account for possible influences.

7.2 Quality Assessment of Household Survey Data

In order to assess the quality of the direct observation protocol, questionnaire survey and responses emanating from the interview, I evaluated the agreement of interviewers' questions and responses by re-interviewing 20% of the survey population. As an on-going process during the fieldwork and after, I assessed the characteristics of the household database to identify missing data, completion status of household surveys and response rates in order to make a decision on when I have reached a sample size such that item response for appropriate questions that would be used to develop composite measures representing the environmental and socio-cultural risk variables is met, and gauged the reliability of the multiple questions to appropriately represent the true measure of the variables. These efforts are presented in this section.

7.2.1 Interviewer Agreement

I assessed the percentage of similar responses given by a respondent through the re-certification of 20% of the field assistants' fieldwork (Gisev, Bell et al. 2013). This

yielded 70% to 82% agreement between the four field assistants and myself and an average of 76% agreement across all interviewers. This is a substantial agreement across interviewers and my efforts. I corrected problematic questions during fieldwork to improve on the agreement beyond its current substantially high state.

7.2.2 *Reliability Analysis*

As a first step to deriving “preventative behaviours and level of knowledge” composite variables employed in this research, I assessed the reliabilities of each individual score using Cronbach’s alpha (α). The level of knowledge variable is derived from questions as presented in the methodology chapter (section 4.11.4.2). Though these results have been presented earlier in the methodology chapter, I present them once again in Table 10. Questions used to derive preventative behaviours yields a Cronbach’s α of 0.60 while those used to derive level of knowledge yields a Cronbach’s α of 0.80.

Table 10: Internal reliability assessment of composite variables

<i>Indicator Measure</i>	<i>Cronbach's α</i>	<i>Bryman (2012)</i>
Variables associated with Preventative Behaviours	0.6	Satisfactory
Variables associated with Level of Knowledge	0.8	Very good

7.2.3 *Analysis of Missing Data and Response Rates*

This section describes and discusses the datasets arising from the household questionnaire and direct observation survey of the main study and the process of arriving at a final working sample size, as well as the similarities/dissimilarities of between complete and incomplete household datasets of the independent risk variables (IRVs). The final working sample size is 208 and consist only datasets on the households with complete item responses such that new and existing risk variables can be used in the analysis.

In order to meet up the intended 505 samples, we had to visit 859 households³⁹ of which I had no prior estimate of refusal/absence rates because there was not enough information on the population and my calculated sample size of 505 accommodated only item non response and not refusals to participate as described earlier in chapter four section 4.10.1. The 505 participating households represent about 58.8% of 859 households visited of which 248 are male and 258 female main respondents, and only 302 were heads/spouses of households. These were the realities and flexibilities I had to

³⁹ These households were selected randomly using the sampling strategy as described earlier in chapter four (section 4.10.1) for the 505 households. Section 4.10.5 shows how refusals were accommodated in the sampling strategy by moving to the next still randomly selected household.

contain doing field work in an unpredictable context. Though we conducted the data collection both at the weekend and on weekdays, there were still more weekdays than weekend days, which resulted in having to visit many households.

We also interviewed households with more weekday availabilities than weekend ones, which occurred more in Kosofe LGA than in Ikeja LGA. More non-heads of households were the main respondents from households visited on a weekday in Ikeja LGA than in Kosofe LGA. Often, heads of households in Ikeja LGA were away at work on weekdays and more accessible at the weekends while in Kosofe LGA, more heads of household/spouse tended to be more at home in the weekdays. We also experienced less resistance to participation in Ikeja LGA than in Kosofe LGA.

Table 11 is a breakdown of completion status for groups of household data. The participating households recorded various response rates for different sections of questions in the questionnaire survey and direct observation protocol. From the 505 households that attempted the survey, we succeeded in gathering representative environmental observation data from only 346 (68.5%) using direct observation, and with the questionnaire survey we had multiple item response levels for groups of covariates. The response rate for key categories were: economic characteristics (412, 81.6%); migration (424, 84%); housing and household composition (394, 78.01%); and 302 (59.8%) of the respondents were heads/spouses of households. Twelve respondents withdrew their consent during data verification and were eliminated from the study.

I focus on explaining the ecology of urban malaria using a multivariate theoretical framework. To achieve this, it was then necessary to retain as much information as possible that would measure all the necessary variables appropriately. It was also important that this information was from similar and the most informed response sources, as suggested by Fowler (2009) and employed by Lowassa *et al.* (2012) in a similar study. The unit of study is the household, and Fowler (2009) recommends using a household member with the greatest knowledge under such situation. In this study I have preferentially selected and used the spouse/head of household that have this attribute, and only in their absence an adult at least 18 years old. I worked with Fowler (2009) recommendations and utilised data from only heads of household. These considerations have led to multiple item response rates for the covariates.

Table 11: Questionnaire response rates and list-wise deletion

<i>Sample Size of Interviewed Households</i>	<i>505</i>	<i>100%</i>
Environmental observation using direct observation protocol	159/ 346	68.50
Questionnaire survey		
□ Economic characteristics	093/ 412	81.60
□ Socio-demographic	011/ 494	97.80
□ Migration	081/ 424	84.00
□ Malaria and KAP	071/ 434	85.90
□ Housing	111/ 394	78.01
Heads/spouses of household	203/ 302	59.80
Withdrawal from study	493/ 012	2.40
Completed questionnaires and observation with spouse/heads of household as main respondent	297/ 208	41.00

N.B. Values in bold are the actual number of participating households

I struck a compromise between the required covariates needed to test and apply the theoretical framework, data gathered on households where the main respondent was the spouse/head of household (for uniformity) and the most appropriate mode of dealing with missing data during logistic regression analysis as utilised in this research.

The most accurate regression approach employs list-wise deletion, which includes in its final model only those cases that contain complete records for every variable (Allison, 2001; Tabachnick and Fidell, 2012). While this method reduces sample size, increases standard errors and thus loss of statistical power in the tests conducted (Olinsky *et al.*, 2003), it is still considered more superior to the dummy variable adjustment that can cause biased estimates of coefficients (Jones, 1996; Olinsky *et al.*, 2003) or the elimination of variables of known causal relationship with the disease. In addition, eliminating core covariates associated with the theoretical framework which have missing data, means not exploring the framework, which is the fundamental basis of this research, to its full potential. Thus, a decision was made to select core variables from the research instruments (questionnaire and direct observation) associated with the human ecology of disease (HED) framework as much as possible, apply a list-wise deletion approach and work with only 208 complete cases related to spouses/heads of households, knowing full well the consequences of small sample sizes and subsets.

I also noted a more incomplete household data collection experience in Kosofe and Ikeja LGAs. Table 12 is the breakdown by LGA of the 505 participating households and the 208 households selected for further analysis. The sample selection bias is obvious in the proportion of sample sizes of participating households.

Table 12: Sample size distribution by household

	<i>Total Sample Size</i>		<i>Final Sample Size</i> ⁴⁰	
	Frequency	Percentage (%)	Frequency	Percentage (%)
Ikeja	232	45.9	110	52.9
Kosofe	273	54.1	98	47.1
Total	505	100.0	208	100.0

The two resulting datasets were compared to each other to examine their similarities/differences in IRVs as a way of assessing the representativeness of the 208 households to the original data. Table 13 shows the results for statistically significant IRVs of comparing the final variables' datasets used for further analysis and the other datasets, characterised by incompleteness, missing values and where the main respondent was not the spouse/head of household (data on 208 households and the other unused 297 households). A χ^2 , Mann-Whitney U and T tests of independence were performed to nominal, ordinal and continuous data respectively. This was to ascertain if there was a significant difference between the two groups of data for multiple IRVs. According to Table 13, the relation between education of head of household (education of H of HH) (U=27,669, p=0.033, Z=-2.122), distance to water (DW) (U=26,213, p=0.003, Z=-2.985), LGA χ^2 (9.481, p<0.002), religion χ^2 (21.3, p<0.00) and ethnicity χ^2 (28.57, p<0.00) differ significantly across these datasets as presented in the table but do not differ significantly across other variables that include elevation, Normalised Difference Vegetation Index (NDVI), wealth and migration/travel history (these are not presented in the table, as they are not statistically significant). The distribution of ethnic groups are such that tribes like the Hausas, indigenous Awori's, minority tribes of Nigeria and non-Nigerians have right from the onset represented a smaller percentage of 505 surveyed households this is same for religious groups like the Muslims, atheists and traditionalists. In the demography of Lagos state these ethnic groups account for a smaller percentage of the residents while the official distribution of religious groups is unknown. However, these religious and ethnic groups have accounted for a minority size in the original sample of 505 households and not surprising they have been impacted the greatest in the sample size reduction. I have no explanation for the pattern.

With the sample size reduction, the data still reveals more similarities than dissimilarities amongst the two groups. I made a decision to select as many core variables as possible associated with the HED framework, apply a list-wise deletion

⁴⁰ Final sample size after elimination of incomplete household data

approach and work with only 208 complete cases related to spouses/heads of households, knowing fully well the consequences of small sample sizes and sample bias. Therefore, this should be remembered throughout in the preclusion of finding significant relationships or otherwise in the analysis conducted in the subsequent sections.

Table 13: Comparison between final complete datasets with spouse or head of household as main respondent and incomplete datasets/complete datasets where main respondent is not head of household for statistically significant IRVs

<i>Variables/Statistics</i>	<i>Mann-Whitney U</i>	χ^2	<i>p-value</i>
Place of Residence LGA		9.481	0.002
Ethnicity		28.57	0
Religion		21.3	0
Distance to Water (DW)	26,213		0.003
Education of H of HH	27,596		0.03

H of HH: Head of household

Figure 57 is a map showing the distribution of self-reported malaria in 208 households located in these areas. Of the 208 households interviewed, 142 (68.27%) of them had experienced malaria in the last year, while 66 (31.73%) had no account of malaria in the household. This means that the infection rate in the population was about 68.27%. Out of 142 households with malaria, only 63 (44.4%) visited the HCF and the remaining 79 (54.5%) used home treatment. The dataset will be utilised in examining the ecology of urban malaria in Ikeja and Kosofe LGAs taking into consideration behavioural and environmental characteristics, which will be described in detail in the next sections.

7.3 Frequency Distribution and Percentage Infection Levels in Households

In this section, I present the frequency distribution statistics and percentage infection levels of malaria infection according to IRVs of surveyed households. The infection rate for the sample population is 68.27%.

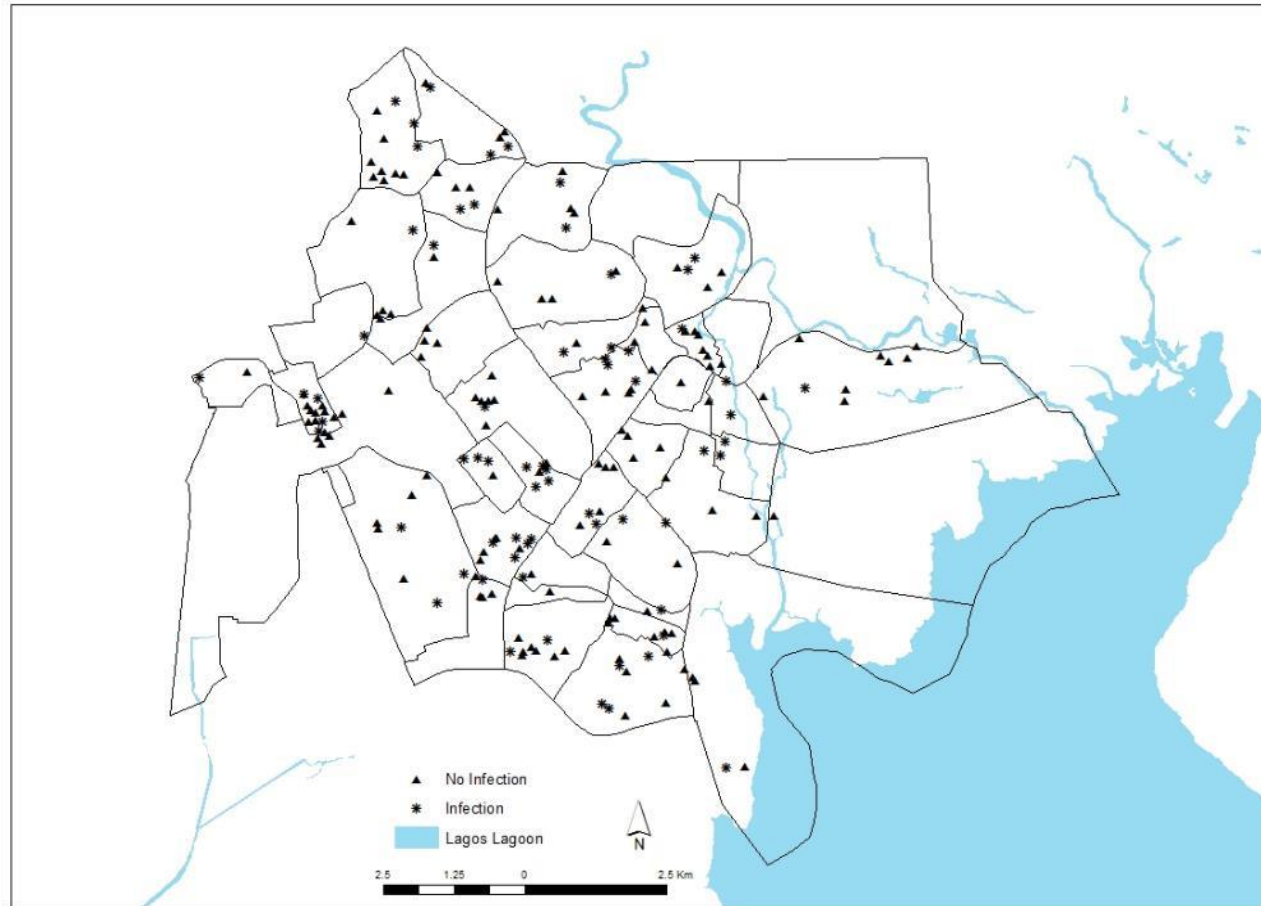


Figure 56: Location of final sample employed in further analysis showing the distribution of self-reported malaria infection⁴¹

⁴¹ Exact geographic locations of households are displaced to preserve anonymity of respondents.

7.3.1 Behavioural Risk Variables

According to Table 14, three aspects of Knowledge Attitude and Practice (KAP) were examined, measuring level of knowledge, belief as attitude and preventative behaviour. From the table, while the percentages of infection are mainly below or about that of the sample household for level of knowledge, those without a belief and households with very good preventative behaviours have infection levels above that of the population.

The highest ranks of education of (higher education (78.46%)), wealth of (very high wealth (83.33%)) and occupation of heads of household engaged in semi-professional and professional occupations (74.29% and 85.71% respectively) emerge with the highest percentages of infection, higher than the study population rate. This includes households with very good preventative behaviours (75.76%). Under some circumstances some ranks may likely report malaria more or less than others as noted in households where the head/spouse is illiterate: 40% with the lowest infection rates.

Wealth, education, occupation and preventative behaviours are positively related to malaria infection, i.e. the higher the rank class, the higher the infection rate, even though the opposite would often be expected, i.e. wealthier households experiencing a lower rate of malaria infection. These results do not appear intuitive but remain unresolved from the literature.

Others include households with members working at night without protection (70.68%), the household's travel history (73.95%) and households with Yoruba and Igbo ethnicity (72.22% and 72.55% percentage infection levels respectively).

It is expected that households with vulnerable members would record high rates of malaria infection than those without, owing to the higher risks of infection they experience. However, this is not so in the sample population. Households with and without vulnerable members record about the same percentage of infection and this is similar to that of the sampled households.

7.3.2 Built Environmental IRVs

According to Table 15, the number of households participating in this study, irrespective of disease status, is almost equally distributed between Ikeja and Kosofe LGAs. With respect to built environmental variables, characteristics such as storing water at home, animal presence, having a household size that is greater than five,

nearest distance to urban agriculture, and poor wall conditions have the highest infection rates: 71.34%, 71.71%, 76.81%, 71.43% and 79.25% respectively.

Table 14: Frequency distribution and percentage infection rate of socio-cultural IRVs and malaria infection in households

<i>IRVs</i>	<i>IRV Classes</i>	<i>Total per IRV Class</i>	<i>% of Infection</i>
Wealth	Very Low	64	65.63
	Low	64	67.19
	Average	52	69.23
	High	16	68.75
	Very High	12	83.33
Education of H of HH	None	5	40.00
	Primary	23	56.52
	Secondary/Diploma	115	66.09
	Higher Education	65	78.46
Occupation rank of H of HH	Student	11	63.64
	Unemployed	14	42.86
	Non-Professional	113	64.60
	Semi-Professional	35	74.29
	Professional	35	85.71
WaNWMP	Yes	133	70.68
	No	75	64.00
Level of Knowledge	Good	10	60.00
	Very Good	198	68.69
Belief	Yes	179	67.04
	No	29	75.86
Preventative Behaviour	Poor	26	61.54
	Good	149	67.79
	Very Good	33	75.76
Ethnicity	Yoruba	108	72.22
	Igbo	51	72.55
	Minority	49	55.10
Religion	Christianity	173	70.52
	Islam	35	57.14
HHWVM	Yes	92	68.48
	No	116	68.10
Migration and Travel History	Travelled	119	73.95
	Did Not Travel	89	60.67

NDVI: Normalised Difference Vegetation Index; H of HH: Head of household; WaNWMP: Working at night without mosquito protection; HHWVM: Household with vulnerable member

The household size varies between 1 and 21, as shown in Table 16, with an average size of approximately five persons per household, while room density ranges between zero and nine with an average room density of about three. When these are related to the historical occurrence of malaria in households under a reclassification into two classes, as shown in Table 15, the percentage of infection in household size > 5 is 76.8% which is higher than that of the study population. This is different for room density.

When I assess storing water at home, irrespective of whether covered or not or changed frequently, I note that households not storing water at home (58.82%) had a lower percentage of malaria infection rates in the last year than those that did, as well as those

having an animal present (58.93%), indicating a possible preference of mosquitoes for domestic animals over humans, as has been found in other parts of Lagos. As these variables have the lowest infection rates, they may be considered less risky.

The percentage of infection associated with the presence of stagnant water and the condition of mosquito protection did not deviate highly from the population level rate. Households with poor mosquito protection maintained about the same level of infection (68.52%) as the study population.

7.3.3 Physical Environmental Variables

According to table 17 describing infection rates of a number of physical environmental IRVs, the range of infection is between 41.08% and 78.57% for households living on a slope of class 5 (4.301–7.7°) and households living in areas within the NDVI class representing free-standing water respectively.

Table 15: Frequency distribution and percentage infection rate of built environment IRVs and malaria infection in households

<i>IRVs</i>	<i>IRV Classes</i>	<i>Total</i>	<i>% of Infection</i>
Place of Residence (LGA)	Ikeja	110	69.09
	Kosofe	98	67.35
Vegetation Presence	Yes	53	66.04
	No	155	69.03
Presence of Stagnant Water	Yes	106	68.87
	No	102	67.65
Water Storage	Yes	157	71.34
	No	51	58.82
Animal Presence	Yes	56	58.93
	No	152	71.71
Household Size	Less than 5	139	64.03
	Greater than 5	69	76.81
Room Density	Below 3	131	68.70
	Above 3	77	67.53
DUA	Near	14	71.43
	Average	45	64.44
	Far	149	69.13
MPC	Poor	108	68.52
	Good	100	68.00
Wall Condition	Poor	53	79.25
	Good	155	64.52

DUA: Distance to Urban Agriculture; MPC: Mosquito protection condition LGA: Local government area

Table 16: Descriptive statistics for built environment IRVs

	<i>Range</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Median</i>	<i>Mode</i>
Household Size	20	1	21	4.99	5.00	4
Room Density	9.00	0.00	9.00	3.0238	3.0000	2.00

In relation to distance to water, households living the farthest distance from water (3001m and above) and those living at a medium distance (661 to 1577m), within different foraging and flight ranges of the vector mosquito, experience the highest percentages of infection, of 75.76% and 70.27%, respectively, compared to households living nearest to water. On the other hand for distance to vector habitat (DVH), households living very near (0–200m), near (201–660m) and far away (1578–3000m) have the highest infection rates for this risk variable. Another risk variable of interest is slope class 1, with households with an infection percentage of 77.78%, while households living in areas with the lowest elevations tending towards sea level have the lowest infection rates for that risk variable.

Table 17: Frequency distribution and percentage infection rate of physical environment IRVs and malaria infection in households

<i>IRV</i>	<i>IRV Classes</i>	<i>Total</i>	<i>% of Infection</i>
DW	Near (0-660m)	74	68.92
	Medium (661-1577m)	37	70.27
	Far (1578-3000m)	64	62.50
	Farthest (3001 and above)	33	75.76
DVH	Very Near (0-200m)	38	71.05
	Near (201-660m)	78	74.36
	Medium (661-1577m)	52	55.77
	Far (1578-3000m)	24	75.00
NDVI	Farthest (3001-4107m)	16	62.50
	Standing water (-1 to 0)	28	78.57
	Soil/urban built-up (0.09 to 0.2)	100	68.00
	Urban & mixed vegetation (0.2 to 0.3)	41	63.41
Elevation	More dense vegetation (0.3 to 1)	39	66.67
	0 to 10m	61	67.21
	11 to 20m	34	61.76
	21 to 30m	41	60.98
	31 to 40m	52	76.92
	41 to 50m	20	75.00
Slope	Slope Class (1) 0–0.70°	45	77.78
	Slope Class (2) 0.701–1.6°	68	66.18
	Slope Class (3) 1.601–2.8°	52	69.23
	Slope Class (4) 2.801–4.3°	26	73.08
	Slope Class (5) 4.301–7.7°	17	41.18

DW = Distance to water; DVH = Distance to vector habitat; NDVI = Normalised Difference Vegetation Index; BSL= Below sea level; SL= Sea level; ASL= Above sea level

0–200m = Anopheles mosquito forage distance in city centre; 201–660m = Anopheles mosquito forage/flight distance in city centre; 661–1577m = flight range; 1578–3000m = flight range in peripheral areas; 3001 and above = flight range in peripheral/rural areas

This section has described the interrelationship between malaria infection in households and physical environmental characteristics. What is obvious from these results is that while some classes of IRVs, such as slope classes 1 and 5, show results in expected directions, there are generally no definite patterns.

The next section examines the correlated relationship between malaria infection in households and the 26 IRVs employed in this thesis, as well as the relationship between the IRVs, in order to ascertain whether there are any high correlations of significance prior to the subsequent regression analysis to be conducted.

7.4 Correlation Analysis

There exists potential for collinearity when examining causal relations such that large standard errors and unreliable coefficient estimates occur with correlated variables in logistic regression results. Spearman's correlation analysis is used to assess this potential between variables prior to their use in a regression analysis, as well as to assess the extent and direction of their relationships. Such knowledge provides a better understanding of the potential influence between IRVs and DVs in the model development process. These results are presented in Table 18 and statistically significant relationships are highlighted in yellow. From the table, I note that IRVs with presumed significant or established relationships with one another or the dependent variable (DV) proved not to. Some interesting patterns are revealed.

Two variables, wall conditions and travel history, are weakly and inversely related to risk of malaria ($r_s = -0.138$, $r_s = -0.141$, respectively; all at $p < 0.05$). Occupation rank and educational qualification of H of HH, on the other hand, are weakly and positively associated with risk of malaria ($r_s = 0.205$, $p < 0.01$; $r_s = 0.173$, $p < 0.05$). This suggests that the variables are potential predictors with some degree of significant contribution to the risk of infection, and thus provide a cue to expected trends in the later logistic regression models. Other IRVs did not show any statistically significant association with malaria in households.

Room density, which is derived from household size, has a positive relationship ($r_s = 0.493$, $p < 0.01$) with each other, while slope and elevation, derived under similar conditions, are not statistically related ($r_s = 0.021$, $p < 0.01$). Logically, NDVI is related to the presence of vegetation around the housing environment ($r_s = 0.326$, $p < 0.01$), distance to water ($r_s = 0.184$, $p < 0.01$) and elevation ($r_s = 0.249$, $p < 0.01$) even though they display weakly positive relationships. This suggests that NDVI is limited in its ability to capture all vegetation presence, perhaps as a result of the spatial resolution of the Landsat imagery used to derive the measure; NDVI is higher where more paved surfaces occur with longer distances from water and with higher elevation. NDVI is positively correlated with animal presence ($r_s = 0.255$, $p < 0.01$). Though this does not present itself

as a logical relationship, what it may depict is that households living in areas with higher NDVI, which corresponds to more paved surfaces, own more domestic animals compared to those in areas with lower NDVI, corresponding to swampy areas.

Rationally, occupation of H of HH is negatively related to room density and water storage ($r_s=-0.235$, $p=0.05$; $r_s=-0.148$, $p<0.01$, respectively) but positively related to education, wealth and elevation ($r_s=0.550$, $p<0.01$; $r_s=0.344$, $p<0.05$; $r_s=0.177$, $p<0.01$, respectively). This signifies that the higher the occupation ranks of H of HHs, the lower the room density and the less likely they would encounter water shortages to require the storage of water at home. It also suggests that heads of household in higher-ranked occupations have better education, are wealthier and live in elevated places while heads of households in lower-placed occupations reside in water logged areas.

Distance to water, as a physical environmental variable, is positively related to elevation ($r_s=0.728$, $n=208$, $p<0.05$) signifying that areas in closer proximity to water bodies are characterised by low-lying elevations that fall below sea level. It is this set of variables that has the highest r_s across all IRVs.

From the results of the correlation analysis, a number of IRVs showed statistically significant relationships with risk of malaria and other IRVs while some did not. None of the relationships between IRVs showed any correlation (r_s) up to the cut-off of ± 0.8 to suggest collinearity and necessitate its removal from further analysis. While there does not exist any correlation above the stated cut-off that may infer collinearity, this may be revealed in standard errors generated in the univariate and multivariate logistic regression equations that I will deal with next. Where there is, it will be made known.

7.5 Univariate Logistic Regression

This section presents the result from a univariate logistic regression analysis targeted at assessing contributory influence of IRVs on risk of malaria infection in households. It is applied as one of the essential prior steps in model building and examining multivariate relationships. Tables 19 and 20 show the results of this assessment for IRVs having p-values ≤ 0.25 and ≥ 0.25 respectively. The tables also show the odds ratios (ORs) and confidence intervals (CIs).

Table 18: Spearman's correlation analysis between environmental and socio-cultural variables and with malaria infection in households

	Malaria	Household Size	Room Density	WaNWMP	Belief	Occupation	Travel History	Education of H of HH	Level of Knowledge	Wealth Class	PB	HHWVM	Slope	NDVI
Malaria	1.000	0.127	-0.015	-0.069	0.066	0.205 ⁺	-0.141 ⁺	0.173 ⁺	0.04	0.06	0.078	-0.004	-0.114	0.073
Household Size	0.127	1.000	0.493 ⁺	0.039	0.002	-0.033	0.031	0.009	0.003	0.219 ⁺	0.126	-0.373 ⁺	0.047	0.025
Room Density	-0.015	0.493 ⁺	1.000	-0.106	-0.126	-0.235 ⁺	-0.094	-0.270 ⁺	0.035	-0.381 ⁺	-0.124	-0.406 ⁺	-0.014	0.121
WaNWMP	-0.069	0.039	-0.106	1.000	0.102	0.067	0.079	0.164 ⁺	-0.112	0.196 ⁺	-0.065	0.003	0.084	-0.055
Belief	0.066	0.002	-0.126	0.102	1.000	0.255 ⁺	0.045	0.244 ⁺	-0.169 ⁺	0.240 ⁺	-0.132	0.079	-0.068	0.091
Occupation of H of HH	0.205 ⁺	-0.033	-0.235 ⁺	0.067	0.255 ⁺	1.000	-0.025	0.550 ⁺	-0.178 ⁺	0.344 ⁺	-0.013	0.053	0.063	0.002
Travel History	-0.141 ⁺	0.031	-0.094	0.079	0.045	-0.025	1.000	-0.014	-0.033	0.161 ⁺	-0.005	0.007	0.180 ⁺	-0.121
Education of H of HH	0.173 ⁺	0.009	-0.270 ⁺	0.164 ⁺	0.244 ⁺	0.550 ⁺	-0.014	1.000	-0.091	0.417 ⁺	0.014	0.007	0.144 ⁺	0.070
LOK	0.04	0.003	0.035	-0.112	-0.169 ⁺	-0.178 ⁺	-0.033	-0.091	1.000	-0.134	0.053	-0.064	-0.097	-0.083
Wealth Class	0.06	0.219 ⁺	-0.381 ⁺	0.196 ⁺	0.240 ⁺	0.344 ⁺	0.161 ⁺	0.417 ⁺	-0.134	1.000	0.149 ⁺	0.052	0.194 ⁺	-0.026
PB	0.078	0.126	-0.124	-0.065	-0.132	-0.013	-0.005	0.014	0.053	0.149 ⁺	1.000	-0.036	0.026	-0.059
HHWVM	-0.004	-0.373 ⁺	-0.406 ⁺	0.003	0.079	0.053	0.007	0.007	-0.064	0.052	-0.036	1.000	-0.054	-0.075
Slope	-0.114	0.047	-0.014	0.084	-0.068	0.063	0.180 ⁺	0.144 ⁺	-0.097	0.194 ⁺	0.026	-0.054	1.000	-0.003
NDVI	0.073	0.025	0.121	-0.055	0.091	0.002	-0.121	0.07	-0.083	-0.026	-0.059	-0.075	-0.003	1.000
DW	-0.003	0.017	-0.133	0.097	0.168 ⁺	0.126	0.051	0.135	-0.076	0.224 ⁺	0.002	0.128	0.097	0.184 ⁺
DVH	-0.077	-0.128	-0.096	0.096	0.145 ⁺	0.12	0.089	0.213 ⁺	-0.059	0.162 ⁺	-0.059	-0.015	0.122	-0.014
Animal Presence	0.122	0.04	-0.008	0.095	0.057	0.101	-0.045	0.108	-0.035	0.067	0.036	-0.126	-0.017	0.276 ⁺
Wall Conditions	-0.138 ⁺	-0.099	-0.293 ⁺	0.117	0.012	0.106	0.082	0.092	-0.131	0.192 ⁺	0.076	0.123	0.057	-0.003
MPC	-0.006	-0.089	-0.213 ⁺	-0.021	0.002	0.087	0.237 ⁺	0.03	-0.009	0.038	-0.01	0.043	0.038	-0.014
VP	0.028	0.016	0.125	0.026	-0.019	-0.017	0.104	-0.008	-0.028	0.046	0.039	-0.099	0.057	0.326 ⁺
Stagnant Water	-0.013	0.007	-0.165 ⁺	0.044	-0.034	0.1	0.201 ⁺	0.131	-0.004	0.239 ⁺	0.114	-0.017	0.155 ⁺	-0.065
Water Storage	-0.116	-0.044	-0.061	-0.079	-0.133	-0.148 ⁺	0.049	-0.072	-0.029	0.055	0.028	0.058	-0.068	-0.025
DUA	0.024	0.032	-0.119	0.014	0.08	0.092	0.05	0.146 ⁺	-0.002	0.245 ⁺	-0.005	0.116	0.225 ⁺	-0.028
Elevation	0.081	0.04	-0.147 ⁺	0.056	0.161 ⁺	0.177 ⁺	-0.006	0.186 ⁺	-0.055	0.196 ⁺	-0.033	0.167 ⁺	0.021	0.249 ⁺
Yoruba	0.088	0.065	0.068	-0.059	-0.029	0.028	0.035	-0.015	-0.081	0.049	0.079	-0.101	-0.05	0.166 ⁺
Igbo	0.052	0.12	-0.025	0.131	-0.004	-0.083	-0.019	0.057	0.076	0.054	-0.033	-0.077	0.07	-0.130
Minority	-0.157 ⁺	-0.199 ⁺	-0.055	-0.063	0.038	0.051	-0.022	-0.04	0.019	-0.112	-0.059	0.198 ⁺	-0.012	-0.063
Christianity	0.108	0.058	0.022	0.043	0.033	0.048	0.077	0.05	0.019	0.019	-0.048	0.065	0.115	-0.086
Islam	-0.108	-0.058	-0.022	-0.043	-0.033	-0.048	-0.077	-0.05	-0.019	-0.019	0.048	-0.065	-0.115	0.086

Table 18 Cont'd: Spearman's correlation analysis between environmental and socio-cultural variables and with malaria infection in households

	DW	DVH	AP	Wall Conditions	MPC	Vegetation Presence	PSW	Water Storage	DUA	Elevation
Malaria	-0.003	-0.077	0.122	-0.138 ⁺	-0.006	0.028	-0.013	-0.116	0.024	0.081
Household Size	0.017	-0.128	0.040	-0.099	-0.089	0.016	0.007	-0.044	0.032	0.040
Room Density	-0.133	-0.096	-0.008	-0.293 ⁺	-0.213 ⁺	0.125	-0.165 ⁺	-0.061	-0.119	-0.147 ⁺
WaNWMP	0.097	0.096	0.095	0.117	-0.021	0.026	0.044	-0.079	0.014	0.056
Belief	0.168 ⁺	0.145 ⁺	0.057	0.012	0.002	-0.019	-0.034	-0.133	0.080	0.161 ⁺
Occupation	0.126	0.120	0.101	0.106	0.087	-0.017	0.100	-0.148 ⁺	0.092	0.177 ⁺
Migration	0.051	0.089	-0.045	0.082	0.237 ⁺	0.104	0.201 ⁺	0.049	0.050	-0.006
Qualifications	0.135	0.213 ⁺	0.108	0.092	0.030	-0.008	0.131	-0.072	0.146 ⁺	0.186 ⁺
Level of Knowledge	-0.076	-0.059	-0.035	-0.131	-0.009	-0.028	-0.004	-0.029	-0.002	-0.055
Wealth Class	0.224 ⁺	0.162 ⁺	0.067	0.192 ⁺	0.038	0.046	0.239 ⁺	0.055	0.245 ⁺	0.196 ⁺
Preventative Behaviours	0.002	-0.059	0.036	0.076	-0.010	0.039	0.114	0.028	-0.005	-0.033
HHWVM	0.128	-0.015	-0.126	0.123	0.043	-0.099	-0.017	0.058	0.116	0.167 ⁺
Slope	0.097	0.122	-0.017	0.057	0.038	0.057	0.155 ⁺	-0.068	0.225 ⁺	0.021
NDVI	0.184 ⁺	-0.014	0.276 ⁺	-0.003	-0.014	0.326 ⁺	-0.065	-0.025	-0.028	0.249 ⁺
DW	1.000	0.394 ⁺	0.098	0.116	0.010	0.115	0.172 ⁺	0.017	0.578 ⁺	0.728 ⁺
DVH	0.394 ⁺	1.000	-0.082	0.124	0.066	-0.059	0.264 ⁺	0.076	0.630 ⁺	0.366 ⁺
Animal Presence	0.098	-0.082	1.000	0.118	0.085	0.267 ⁺	0.010	-0.133	-0.045	0.118
Wall Conditions	0.116	0.124	0.118	1.000	0.386 ⁺	0.013	0.088	0.128	0.092	0.102
Mosquito Protection Condition	0.010	0.066	0.085	0.386 ⁺	1.000	-0.034	0.134	0.011	0.018	0.091
Vegetation Presence	0.115	-0.059	0.267 ⁺	0.013	-0.034	1.000	0.110	-0.051	-0.027	0.132
PSW	0.172 ⁺	0.264 ⁺	0.010	0.088	0.134	0.110	1.000	0.156 ⁺	0.186 ⁺	0.166 ⁺
Water Storage	0.017	0.076	-0.133	0.128	0.011	-0.051	0.156 ⁺	1.000	0.035	0.045
DUA	0.578 ⁺	0.630 ⁺	-0.045	0.092	0.018	-0.027	0.186 ⁺	0.035	1.000	0.567 ⁺
Elevation	0.728 ⁺	0.366 ⁺	0.118	0.102	0.091	0.132	0.166 ⁺	0.045	0.567 ⁺	1.000
Yoruba	-0.146 ⁺	-0.052	-0.020	0.011	0.059	-0.011	0.058	-0.033	-0.167 ⁺	-0.126
Igbo	0.106	0.103	0.119	0.026	-0.034	0.026	-0.045	-0.013	0.203 ⁺	0.079
Minority	0.064	-0.044	-0.097	-0.039	-0.035	-0.013	-0.023	0.052	-0.009	0.069
Christianity	0.041	0.013	0.075	0.032	0.021	0.061	0.107	0.047	0.079	0.097
Islam	-0.041	-0.013	-0.075	-0.032	-0.021	-0.061	-0.107	-0.047	-0.079	-0.097

LOK: Level of Knowledge; PB: Preventative behaviours; VP: Vegetation Presence; DW: Distance to water; DVH: Distance to vector breeding habitat; NDVI: Normalised Difference Vegetation Index; H of HH: Head of Household; WaNWMP: Working at night without mosquito protection; MPC: Mosquito protection condition; PSW: Presence of stagnant water; DUA: Distance to urban agriculture; HHWVM: Household with vulnerable member

As shown in Table 19, one built and two socio-cultural environmental variables are statistically significant at $p < 0.05$. In particular, household size is the most statistically and positively related IRV ($p=0.039$, $OR=1.137$, $CI=1.006-1.284$) as well as travel history to a rural area ($p=0.043$, $OR=1.84$, $CI=1.02-3.32$) in the same direction, while occupation rank of head of household and wall condition follow with $p=0.048$ and $p=0.05$, $OR=2.1$, $CI=1-4.41$ respectively. While occupation rank is inversely significant to malaria infection, wall condition is positively significant. What these results suggest is that the exposure from household size on malaria, though statistically significant, minimally influences the risk of malaria with an OR of almost 1 when compared to wall condition, which is twice as likely to affect malaria infection. Though occupation rank is generally a statistically inversely important variable, households with semi-professional and non-professional occupations are at the greatest risks of malaria over other households where their heads have other types of occupation.

Distance to vector habitats (DVH) has the highest p-value of 0.211, as noted in the reference category, and its OR varied across its sub-categories with the likelihood of contracting malaria highest in households living at far ($p=0.401$, $OR=1.8$, $CI=0.457-7.087$) and near DVH ($p=0.338$, $OR = 1.74$, $CI=0.561-5.4$) that correspond to anopheles mosquitoes' foraging distances. Slope and ethnicity are other IRVs with statistically significant sub-categories and high OR. Slope class 4, for example, has $p=0.041$, $OR=3.878$, $CI=1.059-14.194$, but has the greatest proportion of varied households residing within the slope configuration. The Yoruba ethnic group has a p-value of 0.036 and 2.119 odds of contracting malaria while the Igbo ethnic group has a p-value of 0.07 but a slightly higher (2.153) odds of having malaria over other ethnic groups.

According to Table 20, which describes IRVs with p-values ≥ 0.25 , the "mosquito protection condition" and "households with vulnerable members" categories report the following: $p=0.936$, $OR=1.024$, $CI=0.571-1.837$, and $p=0.954$, $OR=1.017$, $CI=0.565-1.832$, respectively, signifying that the highest IRV p-values have little or no effect on the odds of the dependent variable (DV). On the other hand, working at night without mosquito protection has one of the highest statistical significances and the highest odds of having the disease ($p=0.321$, $OR=1.356$, $CI=0.743-2.474$) amongst the IRV categories.

Table 19: Univariate logistic regression results for IRVs with p-values ≤ 0.25

Independent Risk Variables (IRVs)	<i>p-value</i>	<i>OR</i>	<i>95% CI</i>	
			Lower	Upper
Household Size	0.039	1.137	1.006	1.284
Migration and Travel History	0.043	1.84	1.02	3.32
Occupation Rank of Head of Household				
Professional Occupation	0.048	Reference class		
Student	0.119	0.292	0.062	1.376
Unemployed	0.004	0.125	0.03	0.517
Non-professional	0.022	0.304	0.109	0.845
Semi-professional	0.238	0.481	0.143	1.619
Wall Condition	0.05	2.1	1.001	4.405
Animal Presence	0.081	0.566	0.299	1.072
Ethnicity				
Minority Ethnic Group	0.081	Reference class		
Yoruba Ethnic Group	0.036	2.119	1.049	4.279
Igbo Ethnic Group	0.071	2.153	0.936	4.957
Education of Head of Household				
Higher Education	0.095	Reference class		
Non-literate	0.077	0.183	0.028	1.205
Primary School	0.047	0.357	0.129	0.984
Secondary School/Diploma	0.083	0.535	0.264	1.084
Storage of Water	0.097	1.742	0.904	3.358
Slope				
Slope Class (5) 4.301 - 7.7°	0.113	Reference class		
Slope Class (1) 0.000- 0.7°	0.008	5	1.514	16.51
Slope Class (2) 0.701 - 1.6°	0.064	2.795	0.941	8.303
Slope Class (3) 1.601 - 2.8°	0.043	3.214	1.037	9.963
Slope Class (4) 2.801 - 4.3°	0.041	3.878	1.059	14.194
Religion	0.198	1.642	0.771	3.498
Distance to Vector Habitats (DVH)				
DVH Farthest (3001–6821m)	0.211	Reference class		
DVH Very Near (0–200m)	0.538	1.473	0.43	5.045
DVH Near (201–660m)	0.338	1.74	0.561	5.4
DVH Medium (661–1577m)	0.635	0.757	0.239	2.391
DVH Far (1578–3000m)	0.401	1.8	0.457	7.087

DVH: Distance to vector habitats; Very Near = forage distance (0–200m), Near = forage distance in city centre (200–661m), Medium = forage distance peripheral (661–1577m), Far = flight range (1577–3000m), Farthest = flight range in rural areas (3000–4107m/5422m)

Table 20: Univariate logistic regression results for IRVs with p-value ≥ 0.25

<i>Independent Risk Variables (IRVs)</i>	<i>p-value</i>	<i>OR</i>	<i>95% CI</i>	
			Lower	Upper
WaNWMP*	0.321	1.356	0.743	2.474
Belief	0.346	0.647	0.262	1.601
Vegetation Presence	0.686	0.872	0.45	1.692
Room Density	0.751	0.972	0.818	1.155
Households with Vulnerable Members	0.954	1.017	0.565	1.832
Place of Residence (LGA)	0.787	1.084	0.604	1.945
Level of Knowledge	0.567	0.684	0.186	2.51
Mosquito Protection Condition	0.936	1.024	0.571	1.837
Presence of Stagnant Water	0.85	1.058	0.59	1.897
Preventative Behaviours				
Very Good Preventative Behaviour	0.497	Reference class		
Good Preventative Behaviour	0.242	0.512	0.167	1.572
Poor Preventative Behaviour	0.371	0.673	0.283	1.603
Elevation				
Elevation 41 to 54m (ASL)	0.425	Reference class		
Elevation -11 to 0m (BSL)	0.514	0.683	0.218	2.147
Elevation 0 to 7.6m (SL)	0.322	0.538	0.158	1.835
Elevation 7.6 to 28m	0.283	0.521	0.158	1.713
Elevation 28 to 41m	0.863	1.111	0.335	3.69
Normalised Difference Vegetation Index (NDVI)				
More dense vegetation (0.3 to 1)	0.609	Reference class		
Free-standing water (-1 to 0)	0.29	0.545	0.178	1.675
Soil/urban built-up (0.09 to 0.2)	0.183	0.473	0.157	1.426
Urban & mixed vegetation (0.2 to 0.3)	0.283	0.58	0.214	1.569
Distance to Water (DW)				
DW Farthest (>3000m)	0.593	Reference class		
DW Near (0-600m)	0.473	0.710	0.278	1.809
DW Medium (661m-1577m)	0.607	0.756	0.261	2.191
DW Far (1578-3000m)	0.192	0.533	0.208	1.370
Wealth				
Wealth rank: Very high	0.836	Reference class		
Wealth rank: Very low	0.239	0.382	0.077	1.898
Wealth rank: Low	0.276	0.41	0.082	2.039
Wealth rank: Average	0.337	0.45	0.088	2.293
Wealth rank: High	0.384	0.44	0.069	2.798
Distance to Urban Agriculture (DUA)				
DUA Farthest (> 3001m)	0.811	Reference class		
DUA Near (0-1577m)	0.858	1.117	0.333	3.746
DUA Medium (1577-3000m)	0.555	0.809	0.401	1.634

DW: Distance to water; DUA: Distance to urban agriculture; WaNWMP: Working at night without mosquito protection

While many variables as presented in Table 19 have re-established their statistical significance, others in Table 20 which do not show any statistical significance but are associated with the HED theoretical framework have known causal relationships, as revealed in the review of the literature. They are also of public health importance as observed during fieldwork and in the relative magnitudes of the effect sizes. This evidence will be useful in the development and evaluation of multivariate regression models, as will be embarked upon next.

7.6 Multivariate Logistic Regression Analysis

This thesis develops ten candidate predictive models depicting the ecology of urban malaria. These candidate models are characterised by variables derived from a single vertex or combinations of vertices associated with the HED theoretical framework evaluated in the previous section. The model development process is such that single or a combination of variables of statistical or public health significance associated with the content of these vertices is examined in relation to malaria risks in the household. The variables include behavioural, physical and built environmental variables as well as population characteristics. The results of this effort are presented in Table 21.

7.6.1 Candidate Predictive Models

According to Table 21, candidate predictive model 1 is based on the univariate logistic regression results for all IRVs with a p-value ≤ 0.05 in the previous section. The IRVs that meet this condition are household size, migration and travel history, wall condition and occupation rank of head of household (H of HH). In the table, the occupation rank of H of HH, migration and travel history and household size are statistically significant at $p=0.029$, $p=0.042$, $OR=1.916$, $CI=1.024-3.586$, and $p=0.034$, $OR=1.148$, $CI=1.01-1.30$, respectively, with travel history to a rural area associated with the highest odds of contracting malaria amongst significant variables. The occupational rank that spouses/heads of household are engaged in is generally inversely significant to the risk of malaria. In particular, the unemployed and semi-professional heads of households have a statistically significant relation with the risk of malaria, and when semi-professional is included the relationship is inverse. The wall condition, in terms of the presence of cracks in the walls, though not statistically significant amongst other variables, is associated with the highest OR across the candidate models.

For candidate predictive model 2, the selection of variables for its development is based on all IRVs with p-values ≤ 0.25 in a univariate logistic regression (see previous section). The IRVs include religion, occupation and education of head of household, migration and travel history, household size, wall conditions, storage of water at home, slope, animal presence, distance to vector habitats and ethnicity. Apart from religion ($p=0.04$, $OR=2.764$, $CI=1.047-7.295$), none of the other IRVs are statistically significant, other than sub-categories such as unemployed ($p=0.011$, $OR=0.098$, $CI=0.016-0.584$), households living where slope is between 0° and 0.7° ($p=0.011$, $OR=6.694$, $CI=1.55-28.916$) and 1.6° and 2.8° ($p=0.042$, $OR=4.224$, $CI=1.054-16.932$).

Other notable IRVs are DVH and household size, which, though not statistically significant, have ORs slightly above 1, suggesting little or no influence as IRVs. Migration and travel history, water storage at home, wall condition and the sub-categories of Yoruba and Igbo ethnic groups have ORs above 1, depicting their influence on increased likelihood of malaria.

Candidate predictive model 3 is developed based only on theoretically relevant behavioural IRVs that include education and occupation of head of household, working at night without protection, wealth, KAP (preventative behaviours, belief and level of knowledge), ethnicity, religion, household with vulnerable members and migration and travel history. Ethnicity is the most statistically relevant IRV ($p=0.03$) and being from a Yoruba household ($p=0.01$, $OR=2.968$, $CI=1.293-6.811$) or Igbo ($p=0.065$, $OR=2.439$, $CI=0.946-6.291$) is associated with over twice the odds of having malaria, while migration and travel history ($p=0.0725$, $OR=1.847$, $CI=0.946-3.610$) and religion ($p=0.064$, $OR=2.375$, $CI=0.952-5.926$) are at borderline statistical significance. Working at night without mosquito protection also contributes to increased odds of contracting malaria. Other IRVs such as the level of knowledge, preventative behaviours, belief, occupation rank and education level of H of HH and wealth, though not statistically significant, are associated with decreased odds of malaria.

Candidate predictive model 4 employs physical environment variables which are theoretically relevant to the HED and characterise vector presence. They are slope, NDVI, elevation, DW and DVH, and none of them are statistically significant in this model, despite slope being significant in previous models. However, slope and its sub-categories have the highest odds (approximately three times) of increased risks of malaria infection. DVH is generally associated with increased odds of contracting malaria, except when living 661m to 1577m away from the vector habitat, with a minimal decrease or almost no influence on malaria at an OR of 0.947. Elevation and NDVI, which are important variables from the literature, though not statistically significant, showed an inverse relationship in the model.

Candidate predictive model 5 is based on built environmental IRVs that include animal presence, household size, room density, wall condition, mosquito protection condition, vegetation presence, presence of stagnant water, water storage in the household, distance to urban agriculture (DUA) and place of residence (which means living in either Ikeja or Kosofe LGAs). In Table 21, household size ($p=0.016$, $OR=1.208$,

CI=1.036–1.409) and wall condition ($p=0.02$, OR=2.746, CI=1.172–6.432) are statistically significant; in particular, the odds of contracting malaria is almost three times higher when living in a house with cracked walls. Room density ($p=0.0516$, OR=0.811, CI=0.653–1.006), while statistically significant, is also inversely associated with malaria, as is mosquito protection condition; animal presence and vegetation presence have an inverse but non-statistically significant relationship.

Candidate predictive model 6 is concerned with assessing the relevance of IRVs associated with the built and physical environment. According to Table 21, wall condition, household size and slope category of 1.6 to 2.8° have a borderline statistical significance at $p=0.061$, OR=2.454, CI=0.959–6.278; $p=0.062$, OR=1.173, CI=0.992–1.387; and $p=0.057$, OR=3.916, CI=0.961–15.956, respectively, while the slope category of 0° to 0.7° ($p=0.03$, OR=5.544, CI=1.176–26.135) is the only statistically significant sub-category. These variables, while being statistically significant, also contribute largely to increased odds of malaria infection in the household. Other notable IRVs are storage of water in the house and DW with increased odds of malaria, but at 1578m to 3000m away, DW becomes sharply associated with decreasing OR.

Candidate predictive model 7 is the most theoretically relevant model, with all 26 IRVs associated with the HED framework. The IRVs are those that are behavioural and those associated with the built and physical environment. From the table, a number of observations are made; one of the most important is the number of constituent IRVs that are not statistically significant. The only statistically significant IRVs are household size, Yoruba ethnicity, having an unemployed spouse/head of household and where the spouse/head of household participates in a semi-professional occupation, as well as being resident in areas where the angle of slope ranges between 0° and 2.8° (3 classes of slope). The model is also characterised by large confidence intervals for a number of IRVs, such as place of residence, wealth, slope and elevation, and this raises some uncertainty about how well the IRV predicts the true situation of urban malaria.

Candidate predictive model 8 consists of IRVs associated with socio-cultural and physical environment. In Table 21, the Yoruba ethnic group and unemployed H of HH sub-categories are the only statistically significant IRVs, other than religion, which is at borderline. Wealth has an inverse relationship; education of H of HH is also associated with decreased OR, but this decrease is in the inverse direction, with households where

the head is better educated having less likelihood of decreased malaria risks. Other variables with decreasing risks are level of knowledge, NDVI and DW.

Candidate predictive model 9 uses IRVs from the socio-cultural and built environment vertices of the HED framework as presented in Table 21. Household size, wall condition and ethnicity are statistically significant IRVs associated with increasing odds of malaria. Unemployed and non-professional occupational ranks of heads of household are statistically significant and inversely related to infection; this also applies to other sub-categories. Other IRVs of significance are preventative behaviour, level of knowledge and belief, which are associated with decreased odds of malaria infection; and working at night without mosquito protection, migration and travel history, religion and living closest to urban agriculture, though not statistically significant, are associated with increased odds of contracting the disease.

Candidate predictive model 10 is based on all statistically significant IRVs from previous models and a theoretically relevant and significant interaction term drawn from the IRVs of the HED. A summary of statistically significant IRVs across previous candidate models are slope, religion, ethnicity, occupation, migration and travel history, animal presence, household size, room density, wall condition and water storage. The interaction term is based on human exposure characteristics and the indicator of vector presence associated with the HED theoretical framework and relevant to malaria risks according to the reviewed literature. The main objective of assessing interactions is to see how the joint effect of two exposure IRVs differs from their separate effects.

In candidate models where occupation has appeared, it has featured significantly. Thus an ideal pair of interaction terms would be related to occupation and characteristics around working environments. However this research has not gathered such data and will therefore focus on pairs of IRVs with known causal relationships interacting across behavioural, physical and built environments. The selected interaction terms and their univariate logistic relationships with malaria are presented in Table 22.

Table 21: Ten candidate predictive models with Independent Risk Variables

(IRVs)	Candidate Model 1	Candidate Model 2	Candidate Model 3	CM 4	Candidate Model 5	Candidate Model 6	Candidate Model 7	Candidate Model 8	Candidate Model 9	Candidate Model 10
Place					0.788	0.248	0.094		0.625	
Residence (LGA)					(1.12,0.489-2.566)	(2.76, 0.49 -15.43)	(6.975, 0.719-67.698)		(1.276,0.48-3.395)	
Household Size	0.034* (1.148, 1.01-1.30)	0.167 (1.103, 0.96-1.269)			0.016* (1.208,1.036-1.409)	0.062 (1.173,0.992-1.387)	0.045* (1.283, 1.006-1.635)		0.01* (1.32, 1.067-1.62)	0.034* (1.196, 1.01-1.41)
Room Density					0.0516 (0.811,0.653-1.006)	0.095 (0.814,0.639- 1.037)	0.145 (0.761, 0.527-1.099)		0.097 (0.762,0.552- 1.05)	0.191 (0.845,0.656- 1.088)
Animal Presence		0.366 (0.697, 0.318-1.53)			0.101 (0.552,0.272-1.122)	0.166 (0.569, 0.257-1.263)	0.598 (0.77, 0.291-2.034)		0.495 (0.742,0.315- 1.749)	0.286 (0.659, 0.306-1.419)
MPC					0.454 (0.772, 0.392-1.52)	0.861 (0.932,0.424-2.049)	0.631 (0.798, 0.318-2.005)		0.353 (0.694,0.321-1.5)	
PSW					0.812 (1.083,0.562-2.088)	0.768 (0.895,0.428-1.873)	0.903 (0.947, 0.394-2.274)		0.843 (1.08,0.503-2.317)	
Storage of Water		0.178 (1.777, 0.769-4.10)			0.299 (1.455,0.717-2.953)	0.096 (1.992,0.884-4.487)	0.095 (2.391, 0.858-6.66)		0.444 (1.407,0.587-3.372)	0.156 (1.818, 0.796-4.148)
Vegetation Presence					0.837 (0.926,0.443-1.935)	0.794 (0.895,0.388-2.062)	0.157 (0.458, 0.155-1.352)		0.277 (0.604,0.243- 1.499)	
Wall Condition	0.065 (2.09, 0.96-4.56)	0.076 (2.201, 0.92-5.264)			0.02 (2.746,1.172- 6.432)	0.061 (2.454,0.959-6.278)	0.061 (2.838, 0.954-8.449)		0.027 (2.91, 1.132-7.482)	0.051* (2.323,0.996-5.418)
DUA										
DUA (>3000m)					0.846	0.162	0.236		0.864	
DUA (0 - 1577m)					0.761 (1.246, 0.302-5.149)	0.461 (0.466,0.061-3.541)	0.55 (0.475, 0.041-5.496)		0.624 (1.532,0.279-8.408)	
DUA (1578-3000m)					0.729 (0.846,0.329-2.176)	0.061 (0.275,0.071-1.063)	0.098 (0.241, 0.045-1.298)		0.969 (0.977,0.306-3.119)	
Migration & Travel History	0.042* (1.916, 1.024-3.586)	0.195 (1.59, 0.789-3.209)	0.0725 (1.847, 0.946- 3.610)				0.302 (1.568, 0.667-3.683)	0.263 (1.535, 0.72-3.254)	0.058 (2.059,0.977-4.341)	0.027* (2.171,1.094-4.311)
Level of Knowledge			0.293 (0.438,0.094-2.037)				0.863 (0.851,0.138-5.254)	0.379 (0.47, 0.087-2.529)	0.624 (0.663,0.128- 3.436)	
HHWVM			0.947 (0.977,0.495-1.929)				0.617 (0.788, 0.311-1.999)	0.997 (0.999, 0.475-2.1)	0.622 (0.813,0.356-1.854)	
Belief			0.475 (0.673, 0.227-1.996)				0.784 (0.827, 0.214-3.203)	0.644 (0.756,0.232-2.467)	0.494 (0.665, 0.207-2.135)	
Religion		0.04* (2.76, 1.047-7.295)	0.064 (2.375,0.952-5.926)				0.073 (2.902, 0.907-9.285)	0.059 (2.623, 0.96-7.148)	0.094 (2.364,0.862- 6.477)	0.026* (2.918,1.136-7.495)
WaNWMP			0.383 (1.386,0.666-2.886)				0.348 (1.534, 0.628-3.745)	0.563 (1.27, 0.569-2.819)	0.307 (1.519,0.682-3.385)	
Ethnicity										
Minority		0.162	0.03*				0.099	0.089	0.054*	0.124
Yoruba		0.065 (2.292, 0.95-5.53)	0.01* (2.968,1.293-6.811)				0.037* (3.061, 1.07-8.754)	0.037* (2.635, 1.059- 6.55)	0.019* (2.944,1.197- 7.241)	0.044* (2.412,1.025-5.672)
Igbo		0.163 (2.115, 0.738-6.06)	0.065 (2.439,0.946-6.291)				0.125 (2.564, 0.77-8.541)	0.098 (2.485, 0.845-7.31)	0.101 (2.396,0.842- 6.813)	0.184 (1.934,0.731-5.119)

CM: Candidate model, MDV: More dense vegetation; SW: standing water; U&MV: urban & mixed vegetation; BU: built-up; DW: Distance to water; H of HH: Head of household; WaNWMP: Working at night without mosquito protection; MPC: Mosquito protection condition; PSW: Presence of stagnant water; DUA: Distance to urban agriculture; HHWVM: Household with vulnerable member

Table 21 Cont'd: Ten candidate predictive models with Independent Risk Variables

	Candidate Model 1	Candidate Model 2	Candidate Model 3	Candidate Model 4	CM5	Candidate Model 6	Candidate Model 7	Candidate Model 8	Candidate Model 9	Candidate Model 10
Occupation of HH										
Professional	0.029*	0.157	0.219				0.083	0.146	0.158	
Student	0.068	0.157	0.192				0.174	0.133	0.164	
	(0.223, 0.044-1.12)	(0.229, 0.03-1.766)	(0.303, 0.05-1.824)				(0.215, 0.023-1.968)	(0.218, 0.03- 1.591)	(0.247, 0.034-1.769)	
Unemployed	0.002*	0.011*	0.018*				0.005*	0.01	0.017	
	(0.102, 0.023-0.45)	(0.098, 0.016-0.58)	(0.141, 0.028-0.712)				(0.056, 0.007-0.423)	(0.092, 0.015-0.56)	(0.115, 0.019-0.682)	
Non-professional	0.009*	0.073	0.083				0.033*	0.085	0.039	
	(0.248, 0.087-0.71)	(0.264, 0.062-1.131)	(0.321, 0.089-1.158)				(0.175, 0.035-0.867)	(0.28, 0.066-1.194)	(0.223, 0.054-0.925)	
Semi-professional	0.126	0.158	0.193				0.14	0.179	0.079	
	(0.377, 0.108-1.32)	(0.373, 0.095-1.47)	(0.42, 0.114- 1.55)				(0.313, 0.067-1.463)	(0.364, 0.083-1.588)	(0.292, 0.074-1.155)	
Education of HH										
HE		0.41	0.626				0.508	0.466	0.783	
Non-literate		0.171	0.233				0.38	0.179	0.503	
		(0.196, 0.019-2.02)	(0.26, 0.028-2.384)				(0.291, 0.018-4.58)	(0.192, 0.017-2.131)	(0.424, 0.034-5.219)	
Primary School		0.391	0.348				0.147	0.219	0.336	
		(0.526, 0.121-2.281)	(0.516, 0.13- 2.056)				(0.269, 0.046-1.583)	(0.379, 0.081- 1.782)	(0.475, 0.104- 2.166)	
Secondary School/ Diploma		0.836	0.405				0.32	0.405	0.473	
		(0.879, 0.261-2.97)	(0.626, 0.208-1.882)				(0.471, 0.107-2.074)	(0.584, 0.164-2.072)	(0.631, 0.179-2.221)	
Wealth										
Very high			0.877				0.325	0.875	0.422	
Very low			0.795				0.985	0.709	0.861	
			(0.786, 0.128- 4.835)				(1.024, 0.081-12.972)	(0.669, 0.081-5.51)	(1.203, 0.152-9.49)	
Low			0.655				0.903	0.65	0.997	
			(0.658, 0.105-4.128)				(0.852, 0.064-11.269)	(0.608, 0.071-5.202)	(1.005, 0.121-8.344)	
Average			0.495				0.236	0.441	0.341	
			(0.534, 0.088-3.232)				(0.224, 0.019-2.662)	(0.453, 0.06- 3.4)	(0.385, 0.054-2.738)	
High			0.423				0.321	0.405	0.286	
			(0.437, 0.058-3.316)				(0.246, 0.016-3.916)	(0.378, 0.038-3.727)	(0.3, 0.033-2.739)	
Preventative Behaviours										
Very Good			0.505				0.544	0.6	0.476	
Poor			0.259				0.278	0.328	0.268 (0.453,	
			(0.474, 0.129-1.734)				(0.424, 0.09-1.999)	(0.5, 0.124-2.007)	0.11-1.84)	
Good			0.334				0.616	0.408	0.273	
			(0.612, 0.226-1.657)				(0.749, 0.241-2.324)	(0.639, 0.221-1.849)	(0.555, 0.194-1.589)	
Slope										
Slope 4.3 - 7.7°		0.155		0.474		0.284	0.177	0.487		0.125
Slope 0-0.7°		0.011*		0.153		0.03*	0.022*	0.089		0.361
		(6.694, 1.55-28.92)		(2.745, 0.688-10.948)		(5.544, 1.176-26.135)	(8.626, 1.358-54.803)	(3.834, 0.81-18.086)		(1.891, 0.482-7.42)
Slope 0.70 - 1.6°		0.061		0.396		0.083	0.03*	0.173		0.542
		(3.569, 0.94-13.50)		(1.749, 0.481-6.365)		(3.574, 0.848- 15.067)	(6.727, 1.199-37.743)	(2.808, 0.636-12.39)		(0.70, 0.225-2.188)
Slope 1.60 - 2.8°		0.042*		0.181		0.057	0.018*	0.089		0.463
		(4.224, 1.05-16.93)		(2.361, 0.67-8.319)		(3.916, 0.961-15.956)	(7.695, 1.412-41.934)	(3.479, 0.82-14.668)		(1.495, 0.51- 4.365)
Slope 2.80 - 4.3°		0.131		0.127		0.1	0.165	0.226		0.026*
		(3.13, 0.71-13.732)		(2.947, 0.736-11.792)		(3.447, 0.788-15.07)	(3.234, 0.618-16.925)	(2.538, 0.563-11.45)		(0.179, 0.039-0.811)

CM: Candidate model, MDV: More dense vegetation; SW: standing water; U&MV: urban & mixed vegetation; BU: built-up; DW: Distance to water; NDVI: Normalised Difference Vegetation Index; H of HH: Head of household; WaNWMP: Working at night without mosquito protection; MPC: Mosquito protection condition; PSW: Presence of water; DUA: Distance to urban agriculture; HHWVM: Household with vulnerable member

Table 21 Cont'd: Ten candidate predictive models with Independent Risk Variables

	CM1	Candidate Model 2	CM3	Candidate Model 4	CM5	Candidate Model 6	Candidate Model 7	Candidate Model 8	Candidate Model 9	Candidate Model 10
NDVI										
MDV (0.3 to 1)				0.824		0.795	0.83	0.837		
SW				0.564		0.633	0.781	0.693		
(-1 to 0)				(0.694, 0.201-2.397)		(0.712,0.177-2.872)	(0.794, 0.155- 4.058)	(0.753, 0.184-3.076)		
Soil/urban BU				0.349		0.33	0.427	0.38		
(0.09 to 0.2)				(0.563, 0.169-1.874)		(0.521,0.141-1.935)	(0.541, 0.119-2.462)	(0.541, 0.137-2.132)		
MV & U				0.566		0.469	0.459	0.5		
(0.2 to 0.3)				(0.732, 0.252-2.127)		(0.653,0.205-2.074)	(0.601, 0.156-2.317)	(0.662, 0.2-2.195)		
DW										
DW (> 3001)				0.776		0.326	0.334	0.858		
DW				0.616		0.165	0.524	0.882		
(0-660m)				(1.5,0.308-7.304)		(4.282,0.55-33.319)	(0.62, 0.143-2.698)	(1.121, 0.25-5.034)		
DW				0.926		0.095	0.073	0.874		
(661-1577)				(1.066,0.277-4.105)		(4.704,0.765-28.922)	(0.108, 0.009-1.234)	(0.887,0.203-3.88)		
DW				0.617		0.976	0.095	0.542		
(1578-3000m)				(1.374, 0.396- 4.766)		(1.019,0.294-3.538)	(0.117, 0.009-1.455)	(0.67, 0.184-2.433)		
DVH										
DVH (3001-4107m)		0.787		0.648		0.277	0.343	0.745		
Farthest										
DVH (0-200m)		0.824		0.579		0.955	0.843	0.513		
Very Near		(1.181, 0.272-5.127)		(1.592, 0.308-8.243)		(1.057,0.151-7.385)	(0.789, 0.075-8.332)	(1.861, 0.289-11.963)		
DVH (201-660m)		0.668		0.504		0.812	0.985	0.657		
Near		(1.349, 0.342-5.316)		(1.623, 0.392- 6.719)		(1.21,0.252-5.816)	(1.019, 0.145-7.168)	(1.455, 0.277-7.635)		
DVH (661-1577m)		0.674		0.94		0.193	0.172	0.861		
Medium		(0.742, 0.185-2.976)		(0.947, 0.229-3.914)		(0.33,0.062-1.751)	(0.239, 0.031-1.861)	(0.864, 0.167-4.478)		
DVH(1578-3000m)		0.96		0.391		0.922	0.561	0.836		
Far		(1.045, 0.19-5.756)		(1.982, 0.415- 9.465)		(0.919,0.171-4.947)	(0.543, 0.069-4.262)	(1.217, 0.19-7.772)		
Elevation										
Elevation				0.619		1	0.903	0.849		
41 to 50m										
Elevation				0.343		0.908	0.419	0.56		
0 to 10m				(0.481, 0.106-2.181)		(1.107,0.195-6.274)	(2.319, 0.301-17.849)	(0.604, 0.111-3.281)		
Elevation				0.297		0.868	0.324	0.638		
11 to 20m				(0.447,0.098-2.032)		(1.158,0.205-6.542)	(2.935, 0.346-24.914)	(0.652, 0.109-3.883)		
Elevation				0.453		0.983	0.441	0.882		
21 to 30m				(0.591, 0.15-2.331)		(1.016,0.225-4.59)	(1.994, 0.345-11.517)	(0.889, 0.188-4.214)		
Elevation				0.887		0.951	0.623	0.704		
31 to 40m				(1.099, 0.299-4.042)		(1.044,0.263-4.139)	(1.498, 0.299-7.493)	(1.327,0.308-5.72)		
Slope × HHWVM										
Slope 5 × HHWVM										0.125
Slope 1 × HHWVM										0.361
										(1.891, 0.482-7.42)
Slope 2 × HHWVM										0.542
										(0.70, 0.225-2.188)
Slope 3 × HHWVM										0.463
										(1.495,0.512- 4.365)
Slope 4 × HHWVM										0.026*
										(0.179,0.039-0.811)

CM: Candidate model; MDV: More dense vegetation; SW: standing water; DW: Distance to water; DVH: Distance to vector breeding habitat; NDVI: Normalised Difference Vegetation Index; H of HH: Head of household; WaNWMP: Working at night without mosquito protection; MPC: Mosquito protection condition; PSW: Presence of water; DUA: Distance to urban agriculture; HHWVM: Household with vulnerable member

Table 22: Potential interaction risk variables in a univariate logistic regression

Independent Risk Variables (IRVs)	p-value	OR	95% CI.	
			Lower	Upper
DVH × Preventative behaviour	0.656	0.975	0.870-1.092	
DW × Preventative behaviour	0.593	1.032	0.920-1.157	
NDVI × Preventative behaviour	0.237	1.079	0.951-1.224	
DUA × Preventative behaviour	0.381	1.073	0.917-1.254	
Elevation × Preventative behaviour	0.169	1.07	0.972-1.179	
Slope × Preventative behaviour	0.299	0.947	0.853-1.050	
Vegetation Presence × Preventative behaviour	0.408	1.13	0.846-1.508	
Presence of Stagnant Water × Preventative behaviour	0.904	1.016	0.782-1.322	
Mosquito Protection Condition × Preventative behaviour	0.738	1.048	0.798-1.376	
<i>Slope × Household with vulnerable members</i>	0.009	1.107	0.020-1.569	
DW × Household with vulnerable members	0.867	0.981	0.782-1.230	
DUA × Household with vulnerable members	0.781	1.031	0.830-1.282	
NDVI × Household with vulnerable members	0.833	1.022	0.833-1.254	
DVH × Household with vulnerable members	0.739	0.967	0.794-1.178	
Elevation × Household with vulnerable members	0.779	1.003	0.982-1.025	
Vegetation × Household with vulnerable members	0.567	0.837	0.456-1.536	
Presence of Stagnant Water × Household with vulnerable members	0.885	0.95	0.472-1.912	
Mosquito Protection Condition × Household with vulnerable members	0.803	0.912	0.444-1.875	

From Table 22, only the interaction term (slope × household with vulnerable members) is statistically significant ($p=0.009$, $OR=1.107$, $CI=0.020-1.569$) and this is added to a candidate model made up of all earlier statistically significant variable (see above). From Table 21 above, the interaction term (slope × household with vulnerable members) is broadly not significant ($p=0.125$) but its sub-category (slope sub-category 4 ($2.8-4.3^\circ$) × household with vulnerable members), while inversely statistically significant at $p=0.026$, is not a high-risk variable, with an OR of less than 1. Other significant variables with increased odds of malaria infection are religion, Yoruba ethnicity, wall condition, travel history and household size, ordered using the OR.

The candidate models will be evaluated for model fitness. The most parsimonious will be selected and the contributory extent of its IRVs will then be discussed.

7.7 Candidate Predictive Model Fit, Assessment and Selection

This section is concerned with assessing and selecting the best-fit predictive models from the ten models listed in Table 21. It employs goodness-of-fit measures such as $-2 \log$ likelihood ($-2LL$), R^2 and the Hosmer & Lemeshow (H-L) test and assesses the models percentage predicting ability.

7.7.1 Summary Measures of Goodness-of-Fit

According to Table 23, none of the candidate models has a statistically significant H-L goodness-of-fit test value. This means there is no difference between observed and model-predicted values, implying that the model estimates fit the data at an acceptable level. Candidate model 7, with all 26 IRVs associated with the HED framework, has the best fit of the ten models. It has the lowest -2LL value (192.48) and its two R^2 measures are the nearest to 1. Candidate model 4 on the other hand, composed of only the physical environmental IRVs, has the poorest fit. It is characterised by the highest -2LL value (243.088) and the lowest R^2 values amongst the other models.

Table 23: Summary of goodness-of-fit measures

<i>Candidate Predictive Models</i>	<i>-2LL</i>	<i>Cox and Snell R^2</i>	<i>Nagelkerke R^2</i>	<i>Hosmer & Lemeshow (H-L) Test</i>
Candidate model 7 (theoretically relevant IRVs of HED)	192.480	0.277	0.388	6.589 (p=0.582)
Candidate model 9 (socio-cultural and built environment)	210.379	0.212	0.297	4.139 (p=0.844)
Candidate model 2 (IRV p-values ≤ 0.25 univariate logistic)	212.219	0.205	0.287	4.180 (p=0.841)
Candidate model 10 (IRVs p ≤ 5 in models & interaction)	214.529	0.196	0.275	12.87 (p=0.116)
Candidate model 8 (socio-cultural & physical environment)	214.668	0.196	0.274	3.450 (p=0.903)
Candidate model 6 (physical and built environmental IRVs)	222.106	0.166	0.233	4.986 (p=0.759)
Candidate model 3 (socio-cultural environmental IRVs)	225.935	0.151	0.211	5.375 (p=0.717)
Candidate model 1 (IRV p-value ≤ 0.05 univariate logistic)	234.984	0.113	0.158	5.501 (p=0.703)
Candidate model 5 (built environmental IRVs)	241.165	0.086	0.121	5.515 (p=0.701)
Candidate model 4 (physical environmental IRVs)	243.088	0.078	0.109	8.396 (p=0.396)

Though none of the models has an R^2 value approaching 1, which would signify a highly fitting model, candidate model 7 predicts the highest R^2 and lowest -2LL values. These models will be assessed further by the way they classify the outcome variable.

7.7.1.1 Models Prediction and Classification Capability of Outcome Variable

Table 24 presents the overall percentage capability for each of the ten candidate models to correctly predict malaria-infected households. The null model predicts only 68.3% of the infected households accurately, but the application of each model's IRVs generally improves its percentage capability which has ranged from 69.7% (candidate model 1, with IRVs with p-values ≤ 0.05 in a univariate logistic regression) to 80.8% (candidate model 7, with 26 theoretically relevant IRVs of the HED framework). From the table, it appears that the greater the number of IRVs in a model, the better its predictive power, which applies to candidate model 7 the highest ranking using goodness-of-fit measures.

Table 24: Overall prediction capability of the ten predictive models

<i>Candidate Predictive Models</i>	<i>Predictive Capability (%)</i>
Candidate predictive model 7 (theoretically relevant IRVs of the HED framework)	80.8
Candidate predictive model 9 (socio-cultural and built environment)	76.0
Candidate predictive model 2 (IRVs with p-values ≤ 0.25 in univariate logistic regression)	74.5
Candidate predictive model 8 (socio-cultural and physical environmental IRVs)	74.5
Candidate predictive model 3 (behavioural/socio-cultural environmental IRVs)	74.5
Candidate predictive model 10 (IRVs with $p \leq 0.05$ from all candidate models & interaction term)	73.1
Candidate predictive model 6 (physical and built environmental IRVs)	72.6
Candidate predictive model 4 (physical environmental IRVs)	71.6
Candidate predictive model 5 (built environmental IRVs)	71.2
Candidate predictive model 1 (p-value ≤ 0.05 in a univariate logistic regression)	69.7

While the goodness-of-fit measures and the prediction capabilities of the candidate models still ranks candidate predictive model 7 highest in comparison to the other nine models, I seek the most parsimonious model (i.e. that uses the minimum number of IRVs to explain the dependent variable) to fit the data; because this candidate model 7 employs 26 IRVs. Candidate model 1, which has the fewest IRVs, has only 69.7% predictive accuracy. In the next section, I utilise the Akaike Information Criteria (AIC) as a measure of the relative quality of the candidate models in a trade-off between model fit and complexity defined by the number of IRVs used in each model.

7.7.2 *Candidate Predictive Model Selection using Akaike Information Criteria*

Candidate models 7 and 9 have ranked as the two models with the best fit and predictive capacity (Tables 23 and 24). Even though model 7 ranks top, it is characterised by a large number of predictor IRVs such that it may exert a higher level of complexity or unmanageability when applied. To strike a balance between complexity and predictive ability, this section applies the AIC to evaluate and select the relatively best model. Specifically, it applies the AICc, which is the AIC with a correction factor for small sample sizes and a large number of IRVs, which characterises this research and also considers each model's log likelihood (-2LL). The details of derivation are attached as Appendix XXV while the final result of the best-fit model is presented in Table 25.

According to Table 25, candidate predictive model 2, which ranks third in predictive capability, is currently the relatively best quality model amongst all ten when using an AICc approach. It supersedes candidate model 7, which had the best predictive capability as related above but is now ranked sixth. Candidate model 2 overcomes the large number of IRVs that model 7 has which can suggest over-fitting by employing

only 11 IRVs. Candidate model 2 has an AICc value of 235.565 while model 7 has one of 252.237.

Candidate model 10 is the second relatively best quality model of the predictive models and comprises ten IRVs made up of the statistically significant variables and the interaction term. It has an AICc of 235.645, which is only 0.080 away from the most parsimonious model (candidate model 2). Candidate predictive model 5, with ten predictor IRVs, has the highest AICc and change in AICc relative to candidate model 2.

Table 25: AIC and AICc estimation for ten candidate models

<i>Rank</i>	<i>Model Definition</i>	<i>AIC</i>	<i>AICc</i>	$\Delta AICc$
*1	Candidate Model 2 (IRVs with p-values ≤ 0.25)	234.219	235.565	0
2	Candidate model 10 (IRVs $p \leq 5$ in models & interaction)	234.529	235.645	0.080
3	Candidate model 1 (IRVs p-value ≤ 0.05 univariate logistic)	242.984	243.181	7.6160
4	Candidate model 3 (socio-cultural environmental IRVs)	247.935	249.282	13.717
5	Candidate model 8 (socio-cultural & physical environment)	246.668	249.516	13.951
6	Candidate model 7 (theoretically relevant IRVs of HED)	244.48	252.237	16.672
7	Candidate model 4 (physical environmental IRVs)	253.088	253.385	17.820
8	Candidate model 6 (physical and built environmental IRVs)	252.106	254.606	19.041
9	Candidate model 9 (socio-cultural and built environment)	252.379	257.347	21.782
10	Candidate model 5 (built environmental IRVs)	261.165	262.282	26.717

*Best quality-fit model

The full details of the best-fit logistic regression model (candidate predictive model 2) as a logistic regression equation model are expressed as:

Logit (Probability of malaria infection in the household) = **1.890** + 1.017 (religion) - 1.475 (student) -2.322 (unemployed) - 1.331 (non-professional) - 0.987 (semi-professional) - 1.63 (non-literate) - 0.642 (primary school) - 0.129 (secondary school/diploma) + 0.195 (migration and travel history) + 0.098 (household size) + 0.789 (wall condition) + 0.575 (water storage) + 1.901 (slope class 1) + 1.272 (slope class 2) + 1.441 (slope class 3) + 1.140 (slope class 4) - 0.361 (animal presence) + 0.166 (DVH 0-200m) + 0.3 (DVH 201-660m) - 0.299 (DVH 661-1577m) + 0.044 (DVH 1578-3000m) + 0.829 (Yoruba ethnicity) + 0.749 (Igbo ethnicity)

Equation 5: Relatively best quality Candidate Predictive Model 2

The ORs of the IRVs, as well as their accompanying coefficients that define their direction of influence in the predictive model, are presented as Figures 58 and 59, respectively. What Figure 58 shows is that all IRVs with $OR \geq 1$ (cut-off line in blue) are associated with increased odds of malaria infection, and the greatest odds of having malaria lies with living in areas within slope angle 0° to 0.7° . The increased odds of malaria are associated with other sub-categories of slope, ethnicity (Yoruba, Igbo), religion, and wall conditions. Other IRVs with the lowest ORs of malaria include occupation rank and educational qualification of heads of household, animal presence and DVH (661 to 1577m).

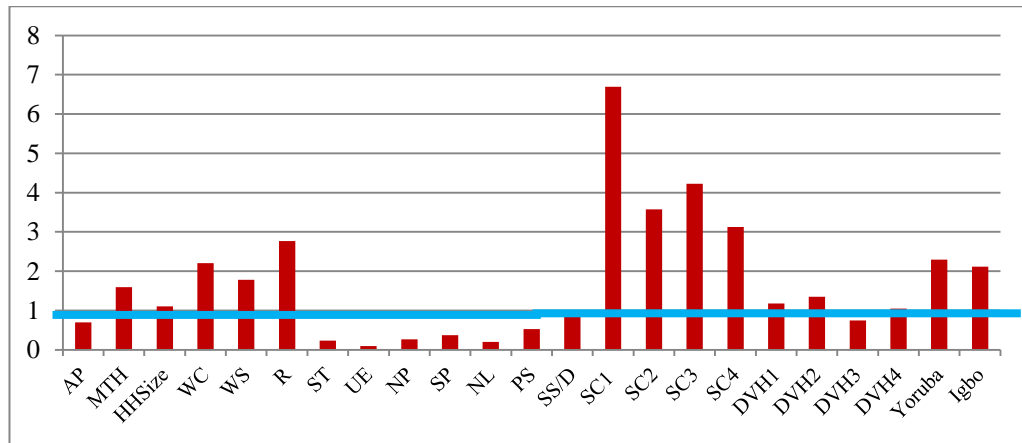


Figure 57: Odds ratios of IRVs in Candidate Predictive Model 2

Key: AP: Animal presence; MTH: Migration and travel history; HHSIZE: Household size; WC: Wall condition; WS: Water storage; R: Religion; ST: Student; UE: Unemployed; NP: Non-professional; SP: Semi-professional; NL: Non-literate; PS: Primary school; SS/D: Secondary school/diploma; SC1: Slope Class (1) 0–0.7°; SC2: Slope Class (2) 0.70–1.6°; SC3: Slope Class (3) 1.60–2.8°; SC4: Slope Class (4) 2.80–4.3°; DVH1: DVH Very Near (0–200m); DVH2: DVH Near (201–660m); DVH3: DVH Medium (661–1577m); DVH4: DVH Far (1578–3000m)

In a similar pattern to the ORs, the coefficients of IRVs in Figure 59 show the direction and magnitude of effect of the IRV in the predictive model. What is obvious is the inverse relationship displayed between malaria infection and education and occupation rank. Of significance is the magnitude of influence exerted by the unemployed heads and those living in locations where the slope angle is 0° to 0.7°. Thus, the higher the occupational rank or education of H of HH, the more likely they are to have or report malaria as was also noted in the percentage malaria infection reported by these IRVs.

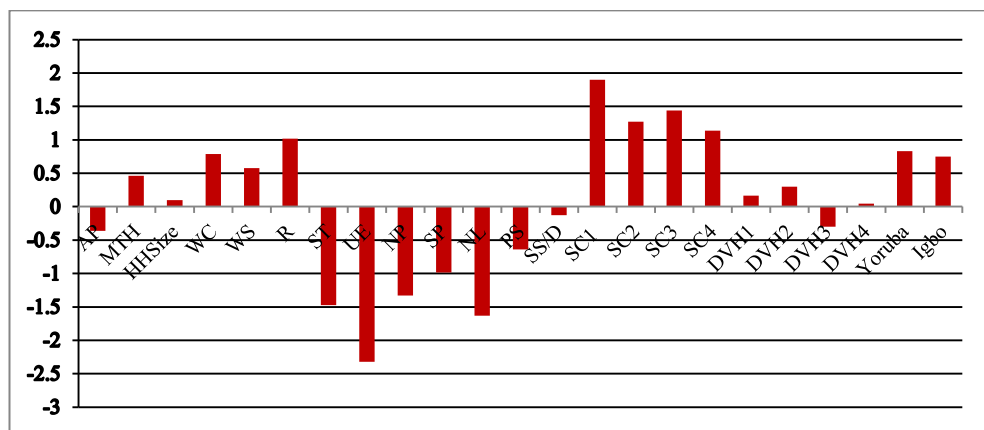


Figure 58: Coefficients of IRVs in candidate predictive model 2

Key: AP: Animal presence; MTH: Migration and travel history; HHSIZE: Household size; WC: Wall condition; WS: Water storage; R: Religion; ST: Student; UE: Unemployed; NP: Non-professional; SP: Semi-professional; NL: Non-literate; PS: Primary school; SS/D: Secondary school/Diploma; SC1: Slope Class (1) 0–0.7°; SC2: Slope Class (2) 0.70–1.6°; SC3: Slope Class (3) 1.60– 2.8°; SC4: Slope Class (4) 2.80–4.3°; DVH1: DVH Very Near (0–200m), DVH2: DVH Near (201–660m) DVH3: DVH Medium (661–1577m); DVH4: DVH Far (1578–3000m)

7.8 Discussion

The urban ecology of malaria entails examining the interrelations of variables contributing to the increasing risk of malaria infection that go on to form focal and heterogeneous spatial patterns of disease in urban environments (Robert *et al.*, 2003).

This study responds to this by interrogating the relationship between urban malaria risks and environmental and socio-cultural variables through the development and assessment of ten candidate predictive models in a subset sample of 208 households. These households have complete information on all 26 IRVs associated with the HED framework, and for consistency reasons, I used data where only the spouse/head of household is the main respondent (Lowassa *et al.*, 2012).

Ten candidate predictive models were assessed for best fit; none of them has a statistically significant H-L test result apart from candidate model 10, which can be further examined for public health significance ($p=0.116$). Despite candidate model 7, with the greatest number of IRVs (26), having the highest predictive capability of 80.8% over candidate model 1, with fewest IRVs (4) and the lowest predictive capacity of 69.7%, both have relative weaknesses/strengths.

Burnham and Anderson (2002) suggest, however, that the best predictive models are robust, parsimonious, and have good predictive capacity. The AIC value for model 2 implies it is the most efficient of all ten models and is characterised by the 11 IRVs with $p \leq 0.25$ that are most relevant for both statistical and public health purposes. These IRVs are religion, occupation rank and education of head of household, migration and travel history, household size, wall conditions, water storage at home, slope, animal presence, distance to vector habitats and ethnicity. They are all associated with the 3 vertices of the HED, similarly to model 7, even though not all the IRVs are statistically significant. Therefore, the model still tests and applies theory. Other IRVs even though not present in candidate model 2, have played prominent roles in malaria infection.

In this study the majority of spouses/heads of households were knowledgeable about malaria symptoms, and mosquitoes as the cause of malaria, and of fever associated with malaria. Indeed, some described malaria in their local dialect with the word “*Iba*”, meaning fever caused by mosquitoes. At the same time, their report shows that households had good and very good knowledge levels to avoid malaria, such that percentage infection was just below (60%) or a par (68.69%) respectively with that estimated in the study sample (68.27%) but also had a large proportion of the belief

factor. This high level of knowledge in urban dwellers and occurrence of belief was also seen in Colombia and Uganda in Nieto *et al.*'s (1999) and Njama *et al.*'s (2003) studies respectively. This is also the same for good preventative behaviours, as reported by Alemu *et al.*'s (2011) study in Ethiopia. One explanation for these trends is that spouses/heads of households have higher levels of education such that it translates to their knowledge and behaviours, but this suggestion should be treated with caution owing to the bias introduced by using a subset of the sample, as reflected in Table 13 for education. Another more plausible explanation is greater access to media information in urban areas, as shown by one of my semi-structured interview participant PT9 with limited English-speaking ability and education (see original quotation in Appendix XXVI).

Translation 1:

My husband insists I should sleep under the mosquito net ... since the radio and the hospital recommend it for the good health of the mother and child ...

(Female, 24 years old)

The more households know about malaria and utilise preventative options, the lower the risks of malaria, as shown in all predictive models including univariate analysis. This direction of relationship is consistent with Njama *et al.*'s (2003); Ngom and Siegmund (2010) and Alemu *et al.*'s (2011) findings, even though their results are statistically significant. The lack of statistical significance in the study may be attributed to the composite measure used to represent preventative behaviour and level of knowledge when compared to these studies that have used single variables. Though both have Cronbach's α of 0.6 and 0.8, indicating above-average and very good internal reliability respectively, Saeed and Ahmed (2003a) and Ngom and Siegmund (2010) studies, utilise a similar composite approach for both variables. Saeed and Ahmed (2003a) had only a borderline influence on malaria infection at $p=0.28$ and 0.26 respectively while in Ngom and Siegmund (2010) household based study it is one of the most important variable.

In addition, what constitutes belief has differed across studies, making comparison difficult. When Saeed and Ahmed's (2003a) multivariate analysis on belief and malaria incidence and this study are compared, though our measures of belief differ, populations in both studies have good preventative behaviour and knowledge, and findings on belief are similarly not statistically significant. My study further notes its decreasing influence

on malaria risks even though the majority of households displayed a belief factor. Some studies have confirmed people's multiple aetiologies of the disease and Esse *et al.*'s (2008) study showed that that was irrespective of socio-economic status. Evidence from my semi-structured interviews in the study area substantiates these findings. Participant (PT6) who has good knowledge of malaria despite being illiterate, report the use of *agbo*⁴² by his wife to prevent malaria transmission between mother and baby during pregnancy, breastfeeding, while generally caring for her new-born and even from external influences. In his words (see Appendix XXVI for original quote):

Translation 2:

Malaria is a small disease for agbo to treat; it is so powerful a remedy that it can eliminate the highest form of disease, witchcraft or bad spirits ... (demonstrates strength with his fists).

(Male, 45 years old)

The inconsistency between these studies and my research work may have resulted from the definition of what constitutes a preventative behaviour, knowledge or belief; methods of data collection; derivation and composition of the IRV; and analysis. Njama *et al.* (2003) and Alemu *et al.* (2011) use single activities, for example the use of insecticide-treated mosquito nets (ITNs), while Saeed and Ahmed (2003a) and Ngom and Siegmund (2010), who on the other hand employ composite measures, derive them differently. While Saeed and Ahmed (2003a) use median values as cut-offs for defining sub-classes, this study often places unequal weights on measures like Ngom and Siegmund (2010) according to their importance, just as for preventative behaviour. When looked at individually, the usage of indoor or outdoor insecticides, and the usage of grids on windows to protect from indoor mosquito biting appear to be more important factors in Ngom and Siegmund (2010) household based study than use of antimalarial which has a very weak contribution in the household predictive model but overall the composite variable preventative behaviour was the best predictor than other IRVs in the model. Despite this, I note the importance of these attributes in disease risks, but the mode of implementation is such that households' contextual situations need further investigation.

Frequently, households who own these preventative measures such as ITNs are unable to use them, even though they are obtained at no cost. The experiences of households in

⁴² Agbo is a herbal remedy believed by the local ethnic groups to prevent and cure a number of illnesses, one of which is malaria.

this respect can be seen in PT9's interview excerpt (see Appendix XXVI for original quote):

Translation 3:

When we moved to this accommodation, we didn't have any bed and I was pregnant. My husband insisted that I would sleep under the mosquito net I was given at the clinic since the radio and the hospital recommend it for the good health of the mother and child. Since we don't have a bed, I sleep on the chair and hang the mosquito net over me. When the child was born, my husband insisted I had to continue to sleep under the net with the baby even though it was on a chair and so uncomfortable. I continued to sleep on the chair carrying my baby on my hands sometimes. The bed was not forthcoming and one day, I moved to the floor and made it my bed. I couldn't bear it anymore. I was so troubled that the baby that God has given me would fall out of my hand all because I wanted to be under a mosquito net which I couldn't find how to fit it because we didn't have a bed and we slept on the floor. I told my husband that nothing would happen to us if we slept on the floor without the mosquito net. I have been sleeping on the floor since then with my baby, we cannot fit the net on the floor ... My husband was given door and window nets that his boss removed from his house when he was replacing his screens. He just fixed them on our windows and doors ... I don't know if the window and door nets help to reduce malaria or mosquitoes, in fact I don't know if anything works including the ITNs. I don't know.

(Female, 24 years old)

Thus, when preventative behaviours are measured using ownership or previous nights' usage, we can often neglect the contextual dynamics that can influence the true measure of that IRV.

Lagos is the largest commercial nerve centre of Nigeria, and also home to high travel and migration frequencies, noted as possible explanations for the shape of its population pyramid, described earlier in Figure 10 (Chapter Four). While this can be a source of state income, it can also be a point of exchange for a number of diseases, vectors and parasites, one of which is malaria, thereby contributing to the high intensities of the disease.

Though the influence of recent travel and migration to rural areas is not statistically significant in the best-fit model, in other candidate predictive models, it is more often than not a strong risk factor for malaria. From this study, about 79.95% of the households with a record of recent travel to rural areas were infected with malaria which is far above the population's average rate, while those without travel history account for less than at 60.67%. This effect persists in the correlation analysis and the univariate regression. It also remains a statistically significant contributor in three out of five multivariate logistic regression models. When examined in candidate models 1 or 9, travel to rural areas is statistically significant. In the presence of other IRVs of both built and physical environmental origin in the other candidate models, even though it is not statistically significant, its public health implications remain conspicuous.

This finding, therefore, has both strong statistical and public health significance in a household and is consistent with findings by Ng'andu *et al.* (1989); Domarle *et al.* (2006); Wang *et al.* (2006c); Baragatti *et al.* (2009) and Peterson *et al.* (2009) in urban locations of Zambia, Madagascar, Cote d'Ivoire, Burkina Faso and Ethiopia, respectively, as well as Tipmontree *et al.*'s (2009) study with displaced peoples at the Thailand–Myanmar border. In this study, someone in almost half of the households made trips to the rural areas and the frequency of trips varied according to the season. Evidence from my semi-structured interviews reveal that during festive periods, a number of households spend time in their villages, while some others rotate weekly between their permanent homes on the outskirts of Lagos and their temporary homes in Lagos CBD for economic reasons.

When new migrants relocate from rural to urban areas, their initial or even permanent accommodations are often in informal settlements located in swamps or illegally reclaimed waterlogged areas, and thus characterised by poor drainage solutions. These migrants become part of the cyclic disease movement that may infect those with whom they share homes in the urban locations, places described by Robert *et al.* (2003) as already having a weakened immunity, and the disease continues to spread. This is the potential case in Lagos state. Many illegally reclaimed swamp areas are not recognised by the government, and as such lack in appropriate infrastructure and are often an object of the government's frequent crackdowns.⁴³ This, in addition to urban residents with a history of recent travel to rural areas, once more contributes to the cyclical and spatial movement of the disease, as noted by Meade (1977) and Meade and Emch (2010).

⁴³ This is one of the issues experienced during fieldwork that affected our sample size.

Taking a household scale approach, this study looks at this risk variable in this way: that any member of the household making this rural travel may become part of the disease cycle by carrying the parasite even though doesn't get the disease, and creates another disease cycle in the household that may infect another in that household that never made a journey and as such making that household at risk.

At the same time, in this study, about 54 of the infected households did not travel to rural areas yet accounted for 60.67% of the infection; even though this is lower than the sample population estimate, this indicates some level of intra-urban transmission. The magnitude of this is unclear for various reasons: for example, recall bias may have set in for non-regular travellers and other members of the household, or misclassification and misrepresentation of a travel destination as rural or urban. This uncertainty, in a similar context, was reported by Siri *et al.* (2010) in his study in urban Kisumu, Kenya.

Migration and travel behaviour has been noted across the literature to hold a central place for malaria. In fact, population movement has been cited by a number of authors, e.g. Hay *et al.* (2002a), as an important driver behind the surge in malaria that culminated to the malaria–climate debate. The consequence of rural–urban migration in Sub-Saharan Africa, according to Robert *et al.* (2003), is rapid urbanisation such that urban infrastructures become overburdened and dilapidated, and municipal government initiatives such as water supply pipes or waste management drainage systems become focal vector breeding and malaria transmission sources (see Figure 7, Chapter Two).

Across all analysis in this study, household size and its derivative room density have been consistently important. Household size in the study area ranges between 1 and 21, with an average of five members per household while room density ranges from zero to nine, with an average of about 3.02 per room across households. Percentage of infection is higher in households with more than 5 members at 76.81% but with room density, this is almost similar across these classes (68.7% and 67.53% respectively) and on a par with the sample population's percentage of infection. In terms of correlated associations with malaria, both are at borderline significance, with household size being positively and room density negatively associated with malaria.

In the univariate logistic regression, household size is positively significant and room density is not, but rather shows a decreasing influence on malaria infection. In all the candidate predictive models in which household size has featured, it is statistically significant only in models 1, 5, 7, 9 and 10, and while it is present in the relatively best

quality model (model 2), it is not statistically significant. In model 6, household size is at borderline statistical significance ($p=0.062$), but despite this, it contributes to the increasing odds of the disease, just as with model 2. On the other hand, out of five candidate models in which room density featured, it has always had an inverse influence on malaria infection, and only in candidate model 5, made up only of built environmental IRVs, does it become borderline statistically significant. These directions, as well as the lack of statistical significance, are similar to the percentages of infection recorded for these IRV classes.

The pattern of relationship found in this research between household size and malaria is consistent with some evidence in the literature. Ernst *et al.* (2006) and Siri *et al.* (2010) found household size to be positively and statistically significant in both univariate and multivariate analysis with Ernst *et al.* (2006) study being significant in one year and other years showing an increasing but non- statistically significant influence just as Alemu *et al.* 's (2011) study. With and without statistical significance, these studies have found an increasing influence of household size on malaria. On the other hand, studies such as Messina *et al.* (2011) report little or no influence of this risk variable.

The decreasing impact of room density on malaria is consistent with Ernst *et al.* 's (2009) and Ayele *et al.* 's (2012) findings under statistically significant and non-significant conditions. In this respect, Trape *et al.* (1992) similarly demonstrate how degree of exposure to a persistent anopheles population reduces over a denser human population. Clark *et al.* 's (2008) and Ngom and Siegmund (2010) studies, however, disagrees with this. With Ngom and Siegmund (2010) using a household approach similar to this study and Clark *et al.* 's (2008) employing an experimental design, it is attractive to agree with their findings but the way they have derived their measures differ from my study making comparison difficult thereby meaning the literature is inconclusive on it. More evidence is needed to verify the importance of this variable.

Ethnicity and religion are broad concepts as noted from the literature and could form its own research agenda. They are intertwined IRVs, as they both have an embedded cultural practice, and often they determine the way people interact with the environment. With the way ethnicity and religion differ by locality, its roles and practices are often not captured fully by the literature considering that it is such a broad concept. In this chapter, I have taken an exploratory approach to understand what both mean for malaria occurrence in households in Lagos state with the intention of recommending future studies.

Ethnicity and religion have appeared in six of the candidate models developed, and have high infection rates for the classes stated, but in only two circumstances have they as a category been statistically significant in different models. In the best-fit candidate model, while both had classes with high infection rates for the disease, only religion is statistically significant.

Three ethnic groups appear in the household sample analysed. Yoruba, Igbo and the minority ethnic classes as a new class derived from ethnic groups that were few in number and then grouped together while the religions practised by the sample are Christianity and Islam. In my study, the percentage of infection in the Yoruba and Igbo ethnic groups is about (72%) over that of over minority tribe (55.1%). In Christians it is (70.52%) over households practising Islam (57.14%).

Apart from religion examined in relation to malaria in pregnant women by Okwa, (2003), none of the studies in the literature have looked at these ethnic tribes in my studies in relation to malaria and thus no direct scholarly explanation is evident for patterns revealed. Oresanya *et al.* (2008) study however, though not examining malaria risks but rather uptake of preventative options in religious groups found uptake higher in Christians than Muslims who lived in Southern Nigeria where Lagos is situated due to the sensitisation done in churches. This yet does not present a clear explanation of the direction of relationship between these religious groups and malaria, as my findings and that from the literature show that the use of preventative measures is associated with lower malaria risks. In addition, given that I have a small sample size for the minority tribe and Muslim households, caution should be exercised when looking at this particular relationship given the nature of my sample. The knowledge I have of the locality suggests that future research with a larger sample that looks at behaviours shaped by these variables such as the modes of dressing or place of residence across the religious and ethnic groups could proffer explanations for this pattern just as in Peters (2010) and Panvisavas (2001) as discussed next.

From the malaria literature, scholars have looked at behaviour and immunities that emanate from ethnic and religious groups which influence their risks to malaria. Peters (2010) and Panvisavas's (2001) note that practices of keeping cattle and choice of where to live determine certain religious groups and ethnicities (respectively) risk to malaria and Phillips *et al.* (2009) note that ethnic tribes with ancestral links to tropical countries possessed some historical immunities. While these may not readily apply to my current research, it is still unclear how this direction of relationship with place of

residence, dressing, and historical immunities might emerge, but future research can collect more data and explore this further.

From the percentage of infected households, the highest ranks of the IRV occupation and education of head of household – professional occupation and higher education qualification – is such that they have the highest percentage of infection in a generally decreasing direction. In all the candidate models where occupation rank of spouse/head of household has featured, it has not only been statistically significant but has displayed an increasing inverse effect, such that more evidence is required to fully understand its implications for disease risk. This also applies to the education of the H of HH and wealth with highest wealth rank having 83% infection rate. Households where the heads/spouses engage in non-professional occupations or are unemployed and have lower educational qualifications have recorded the lowest malaria infection. Semi-professional and unemployed heads of household have been above and below the sample population percentage infection level respectively.

These findings on the surface appear counter intuitive. However, the literature is inconclusive on this as findings have differed. Some studies have used education as an economic indicator and when perused at a global scale, low economic status has driven the global regionalisation of malaria (Sachs and Malaney, 2002) and at a smaller scale Baragatti *et al.* (2009) report its association with higher risk of malaria. However, education and occupation are related in this research, as seen in the correlational analysis, and education can be a predictor of occupational class as well as knowledge, attitude and practice, such that heads of households of higher occupation and educational category are able to identify and report the occurrence of malaria than lower categories, not necessarily that they experience the disease more frequently. This finding is similar to those by ter Kuile *et al.* (2003), and Klinkenberg *et al.* (2006) in urban Accra, Ghana, Zanzibar and Tanzania respectively, where decreasing malaria risks are recorded in households where the spouse and head engage in lower occupational and education categories. Ngom and Siegmund (2010) study using a household approach finds a similar pattern of relationship with low income households having lower risks of malaria. My findings show that those with no education have the lowest percentage of infection and students report even higher malaria infection rates than the unemployed. Unemployed households correspond with those with little or no education, indicating a possible influence with level of knowledge with implications for what is reported. This may also have consequences for the direction of the relationship

observed in this analysis. I need more data to check the actual occurrence of malaria using laboratory methods in order to eliminate under or over reporting of malaria in order to confirm the authenticity of my findings.

In this study, the contributory effect of households with persons working at night without mosquito protection is such that households with such a characteristic are at higher risk of malaria; however, this does not appear in the best-fit candidate model, nor is it statistically significant in any of the models in which it appears. Peterson *et al.* (2009) note this as a cause of increased intensity of malaria in adult populations rather than in children. While this is not statistically significant in this study, the percentage infection is slightly higher (70.68%) than the sample average. Further evidence from the study area showed that the majority of households characterised by this live in locations with the least risk for vector presence, which raises the question: “*From where then have these households been infected with the disease?*” In Appendix XXVII, as visually appraised using GIS overlay analysis, the majority of locations of infected households with this characteristic were overlaid with environmental variables associated with vector presence. This is to examine the extent to which environmental factors may have contributed to the risk of disease, or if sources of infection could be linked to the working environment, which is not noted here.

Several physical environmental IRVs at household locations showed that are considered to have a lower attraction of anopheles presence within households were located (a) on steeper slopes with lower accumulations of water, (b) in built-up urban areas and (c) mainly about 1577m away from water bodies which are (d) least characterised by stagnant water or vegetation presence. Background information on Lagos by the Lagos Bureau of Statistics (LBS) (2012) reveals that over 65% of residents are involved in occupations that require them to work outside at night; some of those occupations are shown in Appendix XXVIII. Many of the residents in the study area work full-time in the open air, and others combine their daytime work with evening and night-time open-air trading, transportation, or undertaking security guard services. Some of the night-time working environments have been discussed as part of the interviews undertaken in the pilot study (appendix IX). They show that people cope with the nuisance of mosquito bites and their health implications while undertaking their night-time occupations or enjoying the social life without preventing mosquito bites.

While an entomological survey has not been part of this study, evidence from Oyewole and Awolola (2006) shows that the *anopheles arabiensis* vector species is present in

twice as many numbers outdoors than indoors over other species identified in Lagos. In addition, their biting hours are throughout the night. According to Service (2002), this species is of importance second only to *anopheles gambiae*, the most dangerous of the vector species, and thus can be a risk factor for those undertaking activities outdoors without mosquito protection. This indicates the importance of working environments as contributory to risk of disease, and further examination of working places in this urban area is required to make a conclusive statement.

Storing water at home, wall condition and the presence of animals are important IRVs that appear in the best-fit model. Only wall condition has presented itself as statistically significant in the correlation analysis, univariate and a number of the multivariate candidate models, but none of the others have. The presence of animals overnight in the home has been associated with an increase in the risk of malaria in Siri *et al.* (2010) and Temu *et al.* (2012), but when situated some distance away from the building, the experience is the opposite. This study focused on the presence of animals within the compound, and even though not statistically significant, this is associated with decreased risk of malaria as noted in the percentage infected without any animal presence, as similarly reported by Peterson *et al.* (2009) and Yamamoto *et al.* (2009). In this study, livestock are located within the compound but some distance away from the building; they are thus likely to be within closer foraging distances of the anopheles mosquitoes and therefore the subject of initial feeding by the mosquitoes rather than humans. Being a highly populated urban area, it is also likely that humans are more in number than animals such that ordinarily zoophilic mosquitoes change behaviour to feed on humans (Service and Townson, 2002). This situation is likely to increase human–vector contact, and thus malaria infection, leading to an inverse relationship such that malaria occurs in households that do not have animals present. This study has not differentiated between types and numbers of livestock that other studies such as Peterson *et al.* (2009) and Yamamoto *et al.* (2009) have sometimes found to be associated with increase and decrease with malaria risks.

Wall condition is positively and statistically significant in three out of the six candidate models it has appeared in, and in other candidate models it is, in fact, at borderline statistical significance (e.g. $p=0.065$ to $p=0.076$). It is depicted in this study as the presence of cracks in the wall which create opportunities for entry of mosquitoes into the house, and thus increase vector–human contact. However, Deressa *et al.* (2007) did not find any significant relationship between holes in house walls and malaria infection

in their study in rural Ethiopia. Lindsay *et al.* (2002) argue that irrespective of housing condition and location, avenues for mosquito entry will increase malaria risks in a population. This could have been the case in this study, because the condition of mosquito protection as an IRV is associated with decreased odds of contracting malaria, thereby suggesting the mosquito screens used are in good condition and not an avenue for mosquito entry. A look back at the percentage of infection, shows that while there is a minute decrease, it is almost on a par with that of the study households.

Storing water in the house in domestic containers is associated with an increasing but not statistically significant risk of malaria in households across all candidate models it has appeared in, including the best quality candidate model. More households who store water at home experience malaria than those that do not as noted in the percentage infection, irrespective of whether they use open or closed containers. Domestic containers have been identified by Okogun *et al.* (2003), Adeleke *et al.* (2008) and Olayemi *et al.* (2011) as major vector breeding sources in urban locations in Nigeria, thus suggesting increased malaria risks. Even though this IRV is associated with increased risk, it is not statistically significant, which can be attributed to a number of factors: Storing water at home is a common activity in Lagos state due to the frequent water shortages. The fact that people store water at home does not automatically translate to increased malaria risks, particularly if the water is used up and replaced daily, as there would not be an opportunity for water to stand undisturbed long enough to permit anopheles breeding. If the water container is covered, then humans create a barrier, as Meade and Emch (2010) note as a feature of human behaviour, and as such there will be no opportunity for anopheles mosquitoes to breed, thereby reducing vector–human contact. This research has not directly observed or differentiated this variable in these respects and this may have contributed to the lack of statistical significance, but its importance is thus noted in the percentage of infected households having this characteristic.

The WHO has reported children under the age of five years, pregnant women and non-immune travellers to be most vulnerable to malaria, meaning that they face higher risks of malaria infection than the rest of the population. In this study, this population variable is represented as households with vulnerable members, here depicted as households with children below the age of five years. We could not gather appropriate data on non-immune travellers and pregnant women due to cultural sensitivity and security issues surrounding the questions.

“You see pregnancy you take it, you observe pregnancy you take it, you don’t announce it, you don’t ask about it!”

(Passing comments)

In this study, this variable is noted to display a negative correlation with malaria, at -0.004, even though it is not statistically significant. The frequency distribution of the variable “households with vulnerable members” is such that the percentage distribution of disease is similar across all IRV classes and sample households even though there is a slight difference between the IRV classes and some have higher levels. In a univariate relationship, it is such that almost no effect is noted in the way it determines malaria risks in households. In the multivariate logistic regression, it occurs in four candidate models (3, 7, 8 and 9) that are not statistically significant, and shows a negative relationship with the disease, meaning that households with children below the age of five are at lower risk of malaria when compared to others. Studies such as Peterson *et al.* (2009) in urban locations have shown similar results. They found that children below the age of five were less susceptible to malaria when compared to older populations because they stayed indoors during biting times of mosquitoes, as compared to adults who stayed out late. From the earlier discussion, working at night without mosquito protection is associated with higher malaria risks in older populations with specific occupation types and activities, and such persons have a higher risk of contracting the disease than the ordinarily vulnerable age group. This relates to some of the issues raised by Meade and Emch (2010), on how social norms, local culture and behaviour by certain population groups put them at greater risk than others. Though the variable (populations that are outside at night) has not been separated by gender, it would be worthwhile for future research. Another reason could be that children below the age of five are the greatest users of mosquito bednets than other people in the study.

Five physical environmental IRVs were examined in relation to malaria risks univariately and multivariately in combination and in interactive terms with other variables. The percentage of infection distribution across the IRV classes is such that some classes have both higher and lower rates over that of the sample population, so that their significance in the candidate models follows a similar pattern. Apart from slope, none of the physical environmental IRVs are statistically significant, but have shown a decreasing relationship with the risk of malaria in households. Increasing NDVI value, distance to water, elevation, and distance to vector habitats all have decreased odds of having malaria, and this also applies to each of their sub-categories.

While the sub-category of slope class 4 (households living between 2.8° and 4.3°) of interaction between slope and vulnerability is statistically significant in candidate model 10 in which it features, as a category it was not statistically significant.

Topographic characteristics such as elevation and slope are often associated with malaria risks. Studies such as Ernst *et al.* (2006) and Nmor *et al.* (2013) have related higher elevations and sharper slopes to significantly decreased malaria risks and larval habitat abundance, respectively. However the importance of each variable differs from one ecological setting to another.

In this study, the way slope affects malaria risks across candidate models is such that everyone is at risk of malaria, but this risk decreases in an often irregular manner with increasing steepness. Slope class 1 has the highest percentage of infection while class 5 has the lowest, differing greatly from the sample population. Less steep slopes tend to be associated with areas that accumulate water and land-use types characterised by high moisture content, and as such, become breeding grounds for anopheles mosquitoes. Households in closer proximity are at higher risk of vector–human contact. Even when the NDVI generated in this study is visually examined, NDVI values corresponding to denser vegetation coincide with flatter slopes. Similarly, Nmor *et al.*'s (2013) study reveals a decreasing impact of increased slope angles on the presence of larval breeding habitats and availability, and one such habitat, “vegetation”, has been identified to be an appropriate settlement for the anopheles (Gaudart *et al.*, 2009; Machault *et al.*, 2010). Shallower slopes were characterised by more habitats in both univariate and multivariate analysis, suggesting slope to be of great influence. In this study, the range of steepness of slopes is limited to between 0° and 7.7°, and while households are evenly distributed across this, the percentage of infection differs. Despite this, in candidate model 7, all slope classes are statistically significant – apart from slope sub-category 4 (2.8° to 4.3°) that indicates greater steepness, such that less water is accumulated, which is less favourable for mosquito breeding – but have a percentage of infection that is above normal for the study population. These three slope classes – 0° to 0.7°, 2.8° to 4.3° and 4.3° to 7.7° – need further investigation to clarify these trends.

Elevation, on the other hand, is not statistically significant with malaria risk, even though it often showed both increasing and decreasing effects on malaria infection, depending on the candidate models in which it appeared. From this study, the percentage of infection for households living at elevations 31–40m and 41–50m is higher than that of the sample population while other elevation classes have a lower

percentage. Thus, the generally inverse relationship is noted. In this study, the elevation range is less than 100m (only 50m), which Dambach *et al.* (2012) found to be the point at which a significant effect on malaria is experienced, and as such the discrimination of elevation between households in this study is limited to finding any statistical influence. Similarly in Myers *et al.*'s (2009) study, where the elevation range is 65m, elevation is not statistically influential on malaria risk, but rather the change in elevation corresponding to slope is more influential. In this respect, Balls *et al.* (2004) suggest slope to be more effective over elevation in predicting malaria risk in small lowland areas. Though evidence from the literature suggests slope to be a better predictor than elevation, the interpretation in this study should be treated with caution, owing to the limitation in the sample size such that any discrimination in elevation values between households may have been omitted.

Other physical environmental variables, such as distance to water (DW) and distance to vector habitats (DVH), are not statistically significant in any of the candidate models, but overall show a more or less negative relationship with malaria risk. This is reflected in the percentage of infection in the DW and DVH sub-classes that range from below that of the sample to above it. Findings are inconsistent with other studies such as Clark *et al.* (2008) and Peterson *et al.* (2009), where it has a statistically significant relation with malaria risk. As indicated earlier, results should be treated with caution owing to the reduction in sample size experienced from the incomplete questionnaires such that DW is significantly impacted. The datasets on anopheles vector habitats employed in this study are unconfirmed or from multiple sources generated for other purposes that date as far back as in the 1900s, and as such their currency or accuracy could negatively influence the outcome of this study. This is a weakness of secondary data sources (Paul White, 2010). More data is required to clarify these findings further.

NDVI is used as a surrogate of climate and vegetation cover in this study, and across all candidate models in which it appears, it has emerged as having a negative but not statistically significant association with malaria risk. Increasing NDVI values are related to increasing malaria risk, as reported by Hay *et al.* (1998b) in their studies in East Africa. However, Hay *et al.* (1998b) note that their findings are only applicable in East Africa, where comparable results have emerged for similar studies, but not West Africa, where this study was performed, owing to ecological differences. Findings from this research work, in the same location that examines the relation between malaria and meteorological variables (Chapter Six) did not find any statistically significant relation.

In fact, the directions and sizes of effects of different meteorological variables were often in unexpected directions, as similarly found in this study. Households living in areas where NDVI values represent free-standing water has the highest percentage of infection and corresponds to slope class 1 with a similar percentage, while households living in urban mixed vegetation areas had the lowest percentage of infection. In addition, the calibration of NDVI values in this study is limited and this can constitute a problem in the analysis. This is noted in the discussion of limitations of this study.

7.9 Conclusion

This chapter set out to examine urban ecology of malaria risks through the contributory influences of 26 environmental and socio-cultural IRVs in households in Ikeja and Kosofe LGAs, Lagos state. The strategy employed was to develop, assess and select the best-fit model from a suite of ten candidate predictive models developed on the basis of the HED framework. The emerging best-fit, most parsimonious candidate model (model 2) had a predictive ability of 74.5% and utilised 11 IRVs associated with the physical and built environments and socio-cultural variables. The direction of relationship shown by some IRVs was often unexpected. The analysis showed that religion, unemployed heads of household and some slope classes are statistically significant, while other IRVs, not statistically significant, had public health implications. The IRVs displayed influences on the risk of malaria in households that differed across the models.

One of the least researched variables, working at night without mosquito protection, emerged consistently as being associated with increased malaria risk. When examined further, locations of households where members displayed this characteristic were not only associated with the least risky environment, but household vulnerability was not a risk factor. This means that adults are at greater risk that is likely attributed to activities outside the home. The public health significance of this risk variable has policy implications, and as such, requires additional studies to further document working environments of urban residents.

Households where heads/spouses are in a professional occupation and very high wealth rank households have the highest percentage of malaria infection, while households where the head/spouse has no education have the lowest. As this is an unexpected direction that is different from some of the literature, it may suggest under or over-reporting.

The best-fit model (model 2) with 11 variables, all of which were associated with the three vertices of the HED theoretical framework, tests and applies theory in a way that indicates the relevance of the framework. The HED represents complex human–environment disease interactions, and its suitability for this study indicates how complex urban malaria is; therefore, a holistic approach offered by this framework is the way forward to combat the disease.

Chapter Eight: Discussion

8.1 Introduction

In the last chapter I presented and discussed the influence of environmental and socio-cultural risk variables on the historical occurrence of malaria infection in households in Ikeja and Kosofe LGAs. From the findings, candidate model 2, utilising IRVs such as household size, animal presence, storage of water, wall condition, migration and travel history, religion, ethnicity, occupation and education of spouse/head of household, slope and distance to vector habitats, emerged as the model with best fit.

This chapter ties together the research objectives, review of academic evidence and methods, the main findings and identifies and discusses the strengths and limitations of the study. I begin by summarising the main results, within which I revisit my research objectives, methods applied and main findings. This is followed by a section discussing the strengths and the limitations of the study.

8.2 Summary of Main Results

As outlined in Chapter One, the overall aim of the thesis is to examine the urban ecology of malaria in Lagos state by identifying important variables for the study location from a broad range of variables associated with the theoretical framework of the human ecology of disease, a dominant tradition of the sub discipline of health and medical geography in which I situate my research. Through the application of this framework, I achieved the following objectives:

8.2.1 *Revisiting Research Objectives*

- To examine the quality of malaria infection data and its management and reporting system in Lagos state-owned health care facilities;
- To explore and visualise the spatial and temporal trends of clinical malaria cases under LSMoH;
- To assess the relationship between clinical malaria and meteorological variables in Ikeja and Kosofe LGAs;

- To investigate the urban malaria risks in relation with environmental and behavioural (socio-cultural) risks in households living in Ikeja and Kosofe LGAs.

The thesis is structured around three empirical chapters that respond to each of the defined research objectives (Chapters Five to Seven).

To achieve these objectives, I initiated the study by gathering monthly clinical malaria infection data from all 25 health care facilities reporting data to Lagos State Ministry of Health (LSMoH). I assessed the quality of the data and the LSMoH data management and reporting capability, using an abridged version of the GFTAM data quality tool. I identified and selected two ecologically diverse LGAs in Lagos state characterised by the highest malaria infection rates. I accomplished this task by assessing a ten-year (2000–2009) spatial and temporal trends in clinical malaria infection at the HCFs situated in LGAs across the state using a density-based non-probabilistic algorithm offered by the 3D geovisualisation GeoTIME software. Through this effort, I identified Ikeja and Kosofe LGAs, with over 180% malaria infection rates and diverse ecological attributes, such that they represent the state's infectivity, environmental and socio-cultural outlook. Ikeja and Kosofe LGAs became the main study focus to achieve the subsequent research objectives.

Following the qualitative assessment of the temporal trends in clinical malaria infection in Ikeja and Kosofe LGAs over a period of ten years, I further employed a time-lagged correlation analysis to examine the way meteorological variables are associated with malaria. I utilised four biologically plausible time-lags (zero, one month, two months and three months).

In the same study area, I conducted a cross-sectional study of 505 households to investigate the contributory influence of environmental and behavioural (socio-cultural) risks to malaria in households. The cross-sectional design was made up of a two-phase study consisting of a mixed-methods pilot study and a main study. In the pilot study, I tested 51 questionnaires and used a semi-structured interview to gather behavioural and socio-cultural data from 18 participants. I implemented the findings and experiences gathered in the pilot study to design and conduct a main study comprising a questionnaire survey and direct observation of household environments, GPS mapping to map households and locations of urban agriculture, and interpretation and verification of remote sensing imagery to generate data on climate surrogates (NDVI) and topographic characteristics. The questionnaire survey and environmental investigation

in the main study was performed by four interviewing field assistants and myself. A subset of 208 households from the database of 505 study population were analysed mainly using quantitative methods, such as logistic regression for the household survey owing to the dichotomous nature of the outcome data and categorical nature of some independent risk variables (Hosmer and Lemeshow, 2000; Tabachnick and Fidell, 2012). I applied content analysis to quantitatively assess and interpret the output of the semi-structured interview (Weber, 1990; Bazeley, 2003; Bryman, 2012).

Through the application of these methods within a theoretically driven cross sectional research design, these major results emerge.

The health care facilities under LSMoH are rich in high-precision, current and archived malaria infection data dating as far back as the 1970s. If accessible, this data would be a huge resource in evaluative research on the disease and public health decision-making. However, it is not properly documented or archived, and this inhibits much research that seeks to use it. The datasets have missing values, and demonstrate completeness and accuracy issues, suggesting unreliability. When I assessed the LSMoH's data management and reporting system that generates and reports malaria infection data, I noted redundancy, consistency and reliability issues in the source documentation of patients' records, broken reporting links from the service delivery sites (SDSs) up to the reporting units (Health Services Commission, Vector Control Unit (VCU), the Health Management Information System) at the LSMoH, late reporting, double counting, and poor storage and archival systems for long-term data records. In all, though the system appeared to exhibit some structure, some of the functionalities of the reporting units were not clearly defined. There were issues with redundancy and duplication of efforts. A similar situation has been found by Chilundo *et al.*'s (2004) study in Mozambique with routine malaria data, using a different assessment approach.

In Ikeja and Kosofe LGAs, malaria persisted each month and did not show any seasonal patterns in the period 2000–2009. Throughout this study period, the prevailing monthly climatic conditions in the LGAs were at least 80mm rainfall, 22°C temperature and 49% relative humidity, which have been reported by Craig *et al.* (1999), Okogun *et al.* (2005), Ye *et al.* (2008) and Tay *et al.* (2012) to be within the minimum needed to sustain vector and parasite presence such that malaria transmission occurs all year round. The results of the malaria–climate relationship are unusual, in that none of the monthly meteorological variables (temperature, rainfall, relative humidity, number of rainy days, sunshine duration hours) are statistically related to monthly malaria cases at

all the four time-lags mentioned earlier. The strengths of the relationship are weak in both negative and positive directions and none are statistically significant. This is inconsistent with Ye *et al.*'s (2008) and Li *et al.*'s (2013) findings regarding temperature, relative humidity, sunshine and rainfall in peri-urban Burkina Faso and China, respectively, but consistent with Tay *et al.*'s (2012) study in the urban centre of Kumasi, Ghana on temperature, rainfall and relative humidity. There is no clear explanation for this heterogeneity, which may reflect differences in local climate or local mosquitoes. However, Tay *et al.* (2012) put forward an explanation on the complexity of urban locations such that climate may only make a partial contribution to disease patterns, which thus require further clarification. While this is relevant to Lagos state, I note also that the study area experiences maximum temperatures over 38°C – characteristic of urban heat islands – and higher malaria intensities, but other studies are either situated in smaller tropical urban and peri-urban areas or temperate regions. As Lafferty (2009) states, climate is often not the primary driver of malaria increase. This is an important finding for this urban location given the intense heat experienced and further demonstrates the importance of this study. Future research that looks at how malaria disease thrives in urban heat islands is suggested.

In investigating the influence of environmental and socio-cultural risk variables on malaria through a predictive model of urban malaria ecology, of the ten candidate predictive models developed, candidate predictive model 2, incorporating all IRVs with $p \leq 0.25$, resulted as the best-fit parsimonious model, comprising IRVs as stated in the introduction of this chapter. In this model, only religion, occupation of spouse/head of household and slope are statistically significant. Travel history to a rural area in the last year, wall condition and ethnicity, though not statistically significant in the candidate model, are associated with higher risk of malaria and are consistent with studies such as Achidi *et al.* (2012); Ng'andu *et al.* (1989); Baragatti *et al.* (2009); Kirby *et al.* (2008); Peters (2010) and Siri *et al.* (2010) in the urban populations.

Apart from the IRV variables noted in the best-fit candidate model, one important variable, working at night without mosquito protection, emerged as being associated with increased odds of malaria infection, while households with children had lower odds. Working at night without mosquito protection, particularly in occupations such as night-time trade, security guard or driver of public transport, or participating in the fullness of the social nightlife in Lagos, put household members at risk of the disease, as revealed in the semi-structured interviews. While households with vulnerable members

were expected to report a higher historical occurrence of malaria infections in the household, my findings in this study revealed the opposite. . Households with members working without mosquito protection at night were at higher risk of the disease, which is consistent with Peterson *et al.* 's (2009) findings with adults whose outside activities coincide with mosquito biting times are at higher risks than children. There is a possible shift from home to the workplace as the primary place of malaria infection, with adults being at even greater risk than children, whom the literature has consistently stated to be the most vulnerable population. However, findings from this research must be treated within the strengths and limitations of the study.

8.3 Strengths of Study

This research work has set out to gather and analyse secondary data sources and survey data from a cross-section of households using a mixed-methods approach. This section will focus on discussing the strengths of this study under the two broad headings of data and methods, bearing in mind that there may often be overlaps.

8.3.1 Data

As this research set out to examine environmental and socio-cultural influences on urban malaria risks in Lagos state, its success depended on the availability of appropriate data on the relevant variables to represent the study area.

This study has successfully generated two major spatial database products that did not previously exist, which can serve as a basis for future research and will also have positive public health implications.

While Lagos State Ministry of Health has been described earlier as having a rich source of information on malaria infection, it is all recorded in paper format and stored under conditions that threaten its future availability. This study, in order to achieve research objectives one, two and three, required access to malaria infection data in a format useable for quantitative analysis.

I extracted monthly in- and outpatient malaria infection data from 25 HCFs in Lagos state for the period 2000–2009 from over 15,000 record sheets. This data was integrated with georeferenced HCF data to build and develop from scratch a spatio-temporal malaria infection database. Though the database is incomplete, due to the quality of the data available from LSMoH, this has established a framework upon which future research and data collection can be based. It still presents itself as a rich source of data,

giving details such as age, gender, parasite type, malaria in pregnancy and deaths associated with the disease under in- and outpatient status.

The research has further examined the quality of the malaria infection data and its reporting system and through this generated appropriate quality information on the database. This quality indicator data will be useful to data users such that they are aware of the strengths and limitations of the spatio-temporal data and know at what point to start building from, improving and extending the data resource. It has also provided assessment data on the reporting system such that data custodians can easily pinpoint levels/links at which to improve it. In particular, the evaluation information will be useful to the tool developers as they continue to seek where and on whom to test the newly developed GFTAM data quality tool, designed specifically for malaria. This data will be an asset, and through it they can know the quality of malaria indicator data in Lagos state as well as the workability of the tool.

Owing to the focal and often heterogeneous nature of urban malaria transmission patterns reported by previous studies such as Klinkenberg *et al.* (2005) and Clark *et al.* (2008), studies at local scales are encouraged, but this means acquiring data at these scales for the ultimate understanding of the urban ecology of the disease. This study generated such data at a micro scale for 505 households in Ikeja and Kosofe LGAs, characterising built, physical and socio-cultural environmental variables associated with risks of malaria infection in the geographic location of such households. The development and population of the spatial database relies on the processing and integration of data from multiple sources. This includes remote sensing imageries, entomological studies, a household survey (questionnaire and direct observation), GPS mapping, secondary data sources (e.g malaria infection data) and semi-structured interviews to back data on behavioural and cultural variables. While the DHS surveys gather malaria-related data, this data does not have an appropriate spatial scale to explore urban malaria infection at LGA level such as that this study has generated. Therefore, generating this data source, which overcomes the limitations of DHS data (e.g. coarse spatial scale, limited malaria information and lack of environmental information), would have been impossible without the application of mixed methods in the data generation and processing. The final product is a spatial database characterised by environmental and socio-cultural variables that can be used as a basis to explore and predict urban malaria risks in the study area.

These databases were developed not only for achieving the objectives of this research, but also to allow the exploration of other attributes available in the database and its integration with other datasets. It is hoped that future research and public health decision-makers can build on the spatio-temporal database for further studies.

8.3.2 *Methods*

This research utilises a HED framework to examine the urban ecology of malaria. As a broad and holistic framework, it requires data on 26 IRVs and one dependent variable (DV) associated with the physical and built environment, behaviour, population and health vertices. The datasets are often not derived from a single source or method, and findings from the literature confirm this. For example, to measure nearness to a vector presence associated with the physical environment may require an entomological survey, from which GIS is used to derive proximity to these locations. It may also entail the image classification/processing of remote sensing imageries. In this study, I have employed a mixed-methods approach in a cross sectional research design. In the absence of an entomological survey, I have sourced entomological data from literature reviews and secondary sources of relevant databases as well as remote sensing imageries, DEM and GPS mapping. I used GIS and remote sensing measures to derive, classify and measure these physical environment variables.

On the other hand, I have utilised a household survey consisting of a questionnaire, direct observation and semi-structured interviews to gather data on behaviour, the built environment, population and health. In particular, I used the interviews to gather data on the everyday lives of people and voice their experiences with malaria, TSB, KAP and the coping strategies used to combat the disease and prevent infection. They were analysed using qualitative and quantitative geographic methods.

Through the application of these methods, I obtained reliable cross-disciplinary datasets necessary for the research. Finally, I processed and integrated all quantitative data on the physical, built, behavioural and population aspects of the framework into GIS databases. I used the quantitative data to examine patterns and relationships while I employed the qualitative data to act as a backdrop that explained these patterns, once more accounting for the strength in geographic methods.

8.4 Limitations of Study

As studies have their advantages so also do they have their limitations, which when acknowledged provide a context through which the research is better understood. This section presents and discusses the limitations and how they have impacted on the study.

8.4.1 Research Design

This research employed a cross-sectional study design, which, while affording the opportunity to collect data on multiple variables simultaneously, is limited in a number of ways. Under this design I used a questionnaire survey, direct environmental observation, GIS and remote sensing to gather data on outcome in the form of self-reported malaria and also data on environmental and behavioural variables.

This study has not benefited from a clinical setting, and as such, uses self-reported malaria data rather than laboratory or clinically confirmed malaria data. As the ability of a participant to accurately report malaria is based on the capability to recognise malaria, often through the identification of febrile-like symptoms. This can introduce reliability issues, particularly in populations whose level of knowledge about malaria is low. Though this is not the case in this sample population, identifying malaria using such symptoms is often not accurate, because many other infectious diseases, such as typhoid fever and pneumonia, have similar symptoms. In other cases, it is possible that populations contract malaria without displaying febrile-like symptoms. In addition, the study design is unable to differentiate between the occurrence of mild and severe malaria in households, and therefore, some variables such as access to health care facilities, known to be a predictor of severe malaria, were left unexamined. These conditions may over- or underestimate the true infection level of the disease in a population and, therefore, the way it influences the transmission dynamics is under-investigated.

Owing to the limitations of a cross-sectional research design, data on variables such as drug resistance was not captured, because such data requires a longer time period and a clinical setting to test the variable which the design does not offer. Certain studies have stated drug resistance to be the main cause of malaria increase and resurgence in many parts of Africa and Asia (Hay *et al.*, 2002b; Na-Bangchang and Congpuong, 2007) of which Nigeria is one affected (Sowunmi *et al.*, 2010). As Lagos state reports an increasing incidence in malaria over the last ten years (LSMoH, 2010; 2011), drug resistance is an important variable to examine further. However, the research design does not allow the collection of such data.

Cross-sectional study designs are limited by the fact that data on all variables are gathered at a particular point in time and give no indication of the sequence of events, i.e. whether the exposure variables occurred before, during or after the occurrence of malaria. This being so, I cannot infer or ascertain causal relationships. For example, with travel history being an important variable for the risk of urban malaria, I cannot ascertain if travel occurred before the attack of malaria or whether the household member who travelled and had malaria did or did not have severe malaria or did not partake in other risky behaviours.

Future research should consider an experimental research design as used by Clark *et al.* (2008) to overcome these limitations.

8.4.2 Data Collection

Parts of the field collection context for this research were limited in a number of ways: timing, political environment, available sampling framework and use of multiple interviewers.

The household survey was conducted over weekdays and weekends in places of residence to allow direct observation of the environments around the residences of households, but more weekdays than weekends were spent in the field, so that the population available for interview was mainly made up of self-employed heads of households running businesses from home, or in their absence, other household members. As a result, most heads of households interviewed were mainly from the self-employed, semi- and non-professional occupation groups with less education, less representing the professional occupation class with better education, therefore resulting in a bias towards the former. In addition, where heads of households were away at work and household members responded, these questionnaires were eliminated during the analysis stages, as the target was heads/spouses of households. This had implications for the final sample size and members available for analysis.

In addition, the political situation and flooding during the main study had consequences for the sample size applied in the final analysis. As described in Chapter Four, while they were clear on the study objectives, there was uncertainty within this context, and often they did not respond favourably to some of the questions due to the political circumstances during fieldwork. For example, many respondents did not respond favourably to the direct observation of their household environments and information on economic, housing and health characteristics. These were also some of the households

where heads/spouses were absent for which the respondent household member restricted us collecting environmental and housing data unless the heads were present. The researchers also experienced death threats and flooding in the study area from the Ogun-Osun river basin during fieldwork. This affected follow-up that would have improved the household survey, as the flooding caused households to be displaced, and the researchers had safety concerns due to the aggression shown towards them. Therefore, this study employed only a subset of the sample for major analysis.

Both the timing of the fieldwork and the incompleteness of the household survey resulted in a reduction in the sample size in ways which resulted in bias of the data available for some core independent risk variables, with consequences for data analysis and interpretation of results.

This study employed the use of a self-developed map sampling framework to support field data collection on the households. However, this sampling framework was not exhaustive, owing to the limited data and time available to undertake a complete enumeration of the study population such that they could be sampled appropriately. Consequently, data gathering on households relied on this non-exhaustive sampling framework..

The use of multiple interviewers, though advantageous to this research to overcome cultural and time barriers, had its weaknesses; however, these were minimised by appropriate training. My field assistants administered at least 60 household surveys each, above the level demonstrated by Robert W. Snow *et al.* (2008) and Kearns and Joseph (1993) work to induce fatigue related error. A repeat interview by the PhD researcher with 20% of the interviewed participants revealed an average 76% percentage agreement with the answers derived from the previous interviews conducted by the field assistants. Though above-average values have been recorded in the correlation of responses, theoretically when the 24% representing non-agreement is propagated throughout the whole sample, the results are likely to still have some interviewer variance issues. However, assessing for interviewer agreement during the course of the fieldwork helped to improve question interpretation and, as such, this would in reality be improved to over 76% after implementing the correction from the re-assessment.

8.4.3 Data Limitations

Through the application of multiple methods this research generated rich datasets. However, these are not without their limitations. The spatio-temporal malaria information system generated by this research represents data from only 25 out of over 250 HCFs in Lagos state, because the other HCFs, which are privately owned, do not have data-generation and reporting capacities. The data is also not characterised by place of infection but place of reporting, and as such I cannot follow up environmental risk characteristics associated with the infected persons. This dataset is incomplete: it is not a true representation of the intensity of the disease in the state and, therefore, any analysis performed on it is not generalisable to the population or the state.

Firstly, there are quality issues with the infection data, such as underreporting over the ten-year period, particularly between 2003 and 2007, caused by an inadequate malaria reporting system, as revealed in Chapter Five as well as the sunshine duration data. This weakens the strength of analysis. The large variation in the number of cases complicates the time-lagged correlation analysis, which may have had consequences for the results generated. Secondly, the availability of weekly data, and using the onset date rather than the reporting date (often different to the onset date) would increase the accuracy of the analysis, particularly when relating it to meteorological variables which affects the mosquito species and parasite within periods as short as nine days. In addition, the non-significant association between meteorological variables and malaria would be better analysed by using at least weekly data, or better still daily data, as it takes as little as 6.5 days for effects to be felt at higher temperatures such as that experienced in Lagos state, as reported by Teklehaimanot *et al.* (2004). Thirdly, non-climatic factors – socio-economic factors and other potential confounders such as water from broken pipes, drains and sewerage systems create focal habitats that are sustained from non-rainfall sources – can obscure malaria–climate relationships. With these, I cannot ascertain whether it is only rainfall that feeds into habitats or other water sources. I have not accounted for local mosquito control programmes, which affect the prevalence of vector species, in the analysis due to the difficulties in obtaining such data.

This study employed the use of Landsat imagery from January 2003 with a spatial resolution of 30m to undertake a study in 2010. This was the only good-quality remote sensing data freely available to the study, but the outdatedness of the dataset had implications for the research, because it does not account for current land-use and land-cover conditions and changes that have occurred in some parts of Kosofe LGA. Even

though I performed groundtruthing to update the information and support the classification of vegetation and land cover derived from the datasets, it covered only the areas not affected by the flooding that took place in the study area.

The currency of data also applies to the entomological information used to represent and map vector habitats in the household research. Some of the georeferenced entomological data dates as far back as the 1950s, with positional accuracies of up to 5km, and the study type refers to either the adult anopheles mosquitoes inside the house or its larvae for external habitats such as water sources. It was not always possible to confirm the current vector presence situation in these locations, particularly where positional accuracies are as high as 5km.

I gathered additional mosquito information in Ikeja and Kosofe LGAs during the fieldwork and with expert opinion from the Entomological Unit of the Nigerian Institute of Medical Research. However, we identified the presence of mosquitoes using vector habitats identified from imagery-classified vegetation and land-use types. The mosquito information was not laboratory confirmed, even though the location where the data was gathered has been identified as an anopheles vector habitat. The consequences are such that, when applied in this study, one should take the interpretation of results cautiously, bearing in mind that the vegetation and land use derived from the Landsat imagery is not current and the spatial resolution simplifies the actual situation on the ground. This also applies to the digital elevation model employed in this study.

These limitations with data currency, spatial resolution and verification of anopheles species types can be improved by further groundtruthing, integrating an entomological study, the use of a current remote sensing imagery, and accounting for local terrain variation by using topographic maps.

Data on the household survey is based mainly on historical experience and information on other members of the household; for example, recalling the experience of malaria in the last year, remembering working, behavioural and travel details of household members, etc. While I employ data from only the head/spouse considered to be the best informed person in the household, it is still subject to recall bias or even having the appropriate knowledge about other household members' activities.

This study uses the household as the unit of study but it has not always been possible for the head of household to capture the dynamics of every household member. Where I have attempted to do so, because the data is on the household level, it may not relate to

the member who records the malaria infection, even though I have acknowledged that what it measures translate to a burden on the household and not the individual members.

8.4.4 Methods

This study employed a density-based spatio-temporal exploration and visualisation approach, offered by the GeoTIME software, to detect the locations of elevated malaria infection in space and time. This method stops at identifying locations with elevated disease rates, but does not confirm they are statistically significant, as applied in other approaches such as Kulldorf SaTScan statistics. Consequently, it presents a number of locations of elevated disease rates without stating how statistically significant they are. Therefore, the use of this method to identify HCFs having elevated disease rates and, in turn, using it to select a study area is exploratory using human visual discernment and not statistically led. Where large differences in distances and densities occur in the datasets, as noted in the malaria infection data across HCFs, its results are somewhat subject to further clarification using other methods. In this study, I accounted for this by initially undertaking an annual assessment of total malaria cases per LGA prior to assessing them in space and time.

One of the limitations in adopting a mixed-methods approach is the loss of data that occurs when converting textual qualitative information into quantitative data and vice versa. In this research, I gathered data on TSB, KAP, cultural, social and other aspects of behaviour with respect to malaria using a semi-structured interview. The purpose was to translate information from this source into close-ended questions with answer options, to be used in developing a questionnaire. I employed content analysis, a quantitative method of analysing textual data, to achieve this. This often means deriving one question or one answer option by converting different lengths of interview text e.g. one word, one sentence, one paragraph or a whole interview transcript only to that question or answer option. I lost information in this way, as noted in the loss of the rich dataset which stemmed from my semi-structured interviews.

While I have selected the most parsimonious model from a suite of predictive models using AICc, these models have not been externally validated and tested. As a result, I cannot say with certainty that candidate model 2 (or one of the other models) is the most accurate, only that it is the most parsimonious from a group of models presented. This is to say they require external validation to ascertain their predictive ability.

8.4.5 Results and Findings

Some of the consequences of the earlier strengths and weaknesses listed are that, by applying multiple data collection and analysis methods in a cross sectional study, I am able to examine the influence of the breadth of variables proposed by the human ecology of disease theoretical framework that previous studies have not attempted. The findings showed that some variables reported to increase malaria risks are of mixed statistical significance. Some of these are level of knowledge, preventative behaviours, wall condition, and working at night without mosquito protection. These could have been influenced by mediating or confounding factors that this study has acknowledged but not accounted for. This could also have been caused by the method of derivation of some indicators representing socio-cultural variables.

While ethnicity and religion often emerged as statistically significant, there are weaknesses in the generalisation of this result. This is due to the use of a subset of the sample, in which the ethnicity, religion, distance to water, and education of spouses/heads of households variables were different from those in the main dataset, as a consequence of applying a list-wise deletion approach for missing data and use of household surveys where the main participant was the spouse or the head of household.

Lastly, there is no direct relationship between malaria and climate, but rather between climate and the vector mosquito and parasite. Therefore, the analysis between malaria and climatic variables is based on an indirect relationship. It does not taken into account “in between” factors such as predation, human preventative behaviours, and alternative water sources to sustain vector habitats. These may influence the biology and behaviour of anopheles mosquitoes and parasites and of course the behaviour of humans to influence vector–human contact and, in turn, malaria. The results generated should therefore be treated with caution, bearing in mind their limitations.

8.5 Conclusion

This chapter has discussed the main findings and listed the strengths and weaknesses of the research. One should view these weaknesses within the context of this study; they are not necessarily applicable in similar studies.

Chapter Nine: Conclusion

9.1 Introduction

My thesis set out to explore and examine the influence of a broad range of environmental and socio-cultural risk variables on urban malaria in a case study of Lagos, Nigeria. The aim was to identify variables of great importance for this study location and contribute to better knowledge of the locality as well as urban malaria in general. As part of this broader aim, I assessed quality issues associated with using secondary sourced data in development research. My research has been driven by a number of factors. My local experiences with malaria; the current trends in urban malaria and its increasing burden in Nigeria, the most populous and impacted country despite global reports of declining incidence; and concerns about current global versus local disease patterns. There is a dearth of urban malaria studies employing the breadth of variables that this study uses, despite the apparent advantage of doing so. In addition, little is known about Lagos state, Nigeria a location gradually making its research agenda more publicly accessible. Therefore, my research contributes to knowledge on geographic spaces for engagement through my experiences of doing research and empirical findings that identify risk variables that are important for the disease in this location as well as testing and applying the HED theoretical framework a dominant tradition of the sub discipline.

In the last chapter, I have presented and discussed the main findings, limitations and strengths of my research. In this chapter, I will focus on the main contributions. I recount my experiences conducting this study and set the context from which they bring in shared knowledge of the locality that inform the broader literature on development research and sub discipline of medical geography.

I am a Nigerian. I belong to another tribe outside of Lagos state but have resided in Lagos for up to 20 years thus having good local knowledge of the state including the main language spoken. However, I have been living outside of Nigeria even prior to embarking on my PhD studies. I have expertise that can support the development of the

data infrastructure in Lagos state. In this case I see myself as an “insider-outsider” and I present my learning experiences from this perspectives hoping that researchers within and outside this “box” but doing development research will benefit from the knowledge.

This chapter is thus a convergence of empirical, theoretical and methodological contributions to knowledge and learning experiences that emerge in doing development research. I hope that my documented experiences can shed light on research undertaken in a similar context and enrich the discussion in relevant fields in health/medical geography. In addition to this, I hope my research provides some insights into some of the difficulties that may have held back progress in reducing the burden of malaria at both global and local levels particularly in my case study location.

9.2 Main Contributions to Knowledge

My thesis consist of processes of data collection and empirical analysis in Lagos state, Nigeria and by virtue of its case study location and its sub disciplinary focus engages with health/medical geography as well development research thereby contributing to knowledge from a broad range of perspectives.

My research contributes to the sub-discipline of medical geography by the empirical findings, testing and applying its dominant ecological discourse to examine variables associated with urban malaria predicted to become more common in the future Africa.

Moving away from the empirical to fieldwork experiences, my attempt to gather and derive valid data involved the negotiation of complex relations, interests and situations and logistics. Often these negotiations entailed wearing multiple hats as a “Nigerian”, “a Lagos resident”, “a student”, “an expert”, “a foreigner”, “a research associate at a local university” in order to progress my research work. In a setting transitioning from long term military dictatorship into civilian governance, these challenges range from sourcing and requesting data, gathering primary data, negotiating relationships with local host institutions, working with field assistants, dealing with health and safety issues and negotiation of ethical and practical dilemmas.

9.2.1 Research Culture

During the military regime, most research on Nigeria was published locally and very little was evident in the international arena. The recent transition from military to civilian government has however triggered opportunities for Nigerian researchers to engage internationally and international researchers to participate in the local research agenda. The latest amendment to the Nigerian Freedom of Information Act on 6th June

2011 giving legislative and political freedom to freely access, collect and use relevant Nigerian datasets when implemented will further stimulate these engagements. These changes have slowly opened up new geographic spaces. Despite the opening of new geographic spaces, I note that old geographic spaces subsist. The learning experience in this is that the written importance of official seals of approval, personal contacts and institutional attachments to access, gather data and conduct fieldwork are still paramount in successfully doing development research in Nigeria. This engages with development research literature which highlights similar experiences in doing research in China (Stross, 1985) and Vietnam (Scott *et al.*, 2006).

9.2.2 Institutional and Data Spaces

As a researcher with insider-outsider positionality it was not necessary to have a pre-established contact under the circumstances of Scott *et al.* (2006). However, my experiences showed that even though I had an introductory letter from Newcastle University, it is equally important to seek an affiliation to a local institution and have a personal contact in Lagos prior to embarking on field work. These contacts and affiliations in Lagos are pivotal in coordinating field work logistics. The benefits includes red stamp that provides a local presence that allows you seek attachment to existing projects, gain access to local data custodians, engage field assistants and even have an office meeting space. An introduction letter from my host institution highlighting this local connection and my international status was more influential than a letter from any of the universities showing only a single status. While these institutional contacts are important, additional personal contacts can help negotiate bureaucratic hurdles when accessing government offices.

As my research entails the examination of a broad range of variables, I needed access to data from multiple sources. In the absence of a good data infrastructure or catalogue, knowing the custodians of data requires visiting over 50 offices and can be a time consuming and frustrating task. At this point a personal contact with good local knowledge makes a big difference.

While visiting offices to source data, my international status presented me as an expert with skills and knowledge and this made me attractive to some and to others it shut doors to data. In many instances I had to negotiate these institutional spaces from multiple fronts. For some datasets, I was given permission based on my local presence and affiliation. I used my international status in addition to my personal contacts to negotiate participation in existing projects and benefit from working under their

permission and ethical clearances thereby overcoming the bureaucratic hurdles of seeking individual ethical clearance and permission to access to data.

The learning experience from this is for researchers to constantly reflect on their positionalities while conducting research in these settings and recognize the implications of negotiating multiple positionalities during the research process.

9.2.3 Use of Field Assistants and Deriving Valid Data

Doing development research in a less familiar setting often requires the use of field assistants but the way their individual characteristics can impact on the reliability and consistency of data gathered is less talked about. This is a serious omission that has also been raised by Scott *et al.* (2006) and taking precautions to minimise this, supports the derivation of valid data.

While undertaking the household survey, I set a number of criteria to work with field assistants. I recruited more field assistants than I needed with a minimum credit pass in English language, ability to communicate in Yoruba language the main language spoken in Lagos state and an additional Nigerian language and also the ability to speak Pidgin English. In order to ensure that they interpreted questions consistently, I put them through one week of training consisting theory, role play, use of GPS and maps, health and safety in the field, actual data collection practice and feedback sessions. At the end of the training, I chose to work with university students as the timing of my fieldwork coincided nicely with their long holidays their availabilities were very high. I found them more submissive to learning and taking instructions than the other much matured field assistants. I put my final set of field assistants through another phase of hands on training. They were all aged between 18 and 23 years, of mixed genders and ethnicities.

Throughout the process of field data collection, I put checks in place to ensure we collected valid data. They include meeting field assistants daily, ensuring they give daily feedback, checking their questionnaires periodically, updating their trainings as required and following up incomplete questionnaires. While still on fieldwork I re-interviewed participants and did an initial assessment of the agreement across interviewers' interpretation of questions being administered in the survey. Doing this within the fieldwork helped me to immediately arrest any agreement issues that may invalidate the data being derived.

One important lesson I learnt from the pilot study is asking the contact details of participants even though it is an anonymous survey as this allowed me to follow on problematic questionnaires.

9.2.4 *Fieldwork in a culture in transition*

One of the experiences recounted by Peil *et al.* (1982) in doing development research in Lagos is lack of exposure of the residents to research projects. Meaning that they are not used to research interviews but rather have greater experience of government led data gathering such as population census, tax etc. In the case of government data gathering, residents participate not because they want to, but because they may be deprived of certain rights or services. Government therefore creates some form of unequal power relations with the residents that coerces them to take part in such exercises. For individual projects, they therefore do not make sense of the long unpaid time we put in to conduct “academic” interviews which are of no use to them. This means they are often suspicious that researchers may have some other motives. Under such circumstances, negotiating entry by using institutional frameworks as provided by the Eko Free Malaria Project can give an entry point into research sites. At the same time working under institutional frameworks under political crisis can jeopardise your research, creating health, safety and ethical concerns in research sites. Under such situation, working as an individual researcher becomes a greater advantage but still plagued with trust issues between the participants and the researcher. Lessons from my field work showed that sharing research findings with participants in environments where research culture is poor as I did can help to build trust and create a more conducive environment in the future. The learning experience gained from this is being flexible and gaining as much personal and institution connections that can help navigate your fieldwork space.

Providing project contact details for participants is a double edged sword. While it clarifies the authenticity of projects, breeds trust for participants, it can also become an ethical, health and safety dilemma for the researcher. My learning experience from this is to purchase a telephone line for which you provide the validity duration to participants and after which their communications maybe directed to your institutions. This helps to address health and safety issues with the researcher that may arise while doing fieldwork in difficult settings.

9.2.5 Methodological Contributions

From a methodological point of view, this research engages with sub-disciplinary evolution by utilising mixed methods in data collection, analysis and interpretation to examine the contributory influence of environmental and socio-cultural risk variables on urban malaria risks. The approach draws multiple methods from social and natural sciences to measure, analyse and address a public health problem. These include the development of conventional research instruments from the scientific, social and behavioural disciplines of biology, sociology, epidemiology, geography and mathematics to understand the risks, patterns and complexity of this disease. They were used to design the semi-structured interviews, the structured direct observation, the household survey, remote sensing and GIS data, including secondary data sources. I apply it in the development, assessment and selection of ten candidate predictive models with theoretical origin from the human ecology of disease.

Through this methodological approach, I examine and quantify the impact of various environmental and socio-cultural factors across the candidate models on the increasing risks of malaria transmission, using familiar geographical techniques in ways to further our understanding of the intricacies of urban malaria risks. I measure surrogates of climate around household locations by using remote sensing methods to derive NDVI from satellite images. At the same time, I engage with human expression of place by using people's experiences in their everyday lives and their voices to interpret the public health significances on what preventative behaviours, working at night without mosquito protection, ethnicity, belief and travel behaviours mean for urban malaria in households, which is not made evident through the quantification of relationships.

These combinations of effort rely on the ecological characteristics of the vector and parasite and their interaction with human populations. It is hoped that they will shed more light on the much deeper complexity of the disease from environmental, social, health and geographical perspectives. Through them, I consciously engage with the broader subject of geography, and in particular the sub-discipline, in ways that remain contemporarily relevant and then contribute to growth within the sub-discipline.

9.2.6 Theoretical and Empirical Contributions

My research examines and explores a broad range of variables identified from the literature (see introduction of section 4.10) and then narrows down on important ones for the locality. From the main findings, travel history, education and occupation of H of HH, ethnicity and religion are important risk factors for malaria in HHs in urban

areas. This is true for household size and density, wall condition, having no animals present and water storage at home are associated with increased malaria risks, and slope is partially statistically significant, while households living closest to water (on free-standing water) have a high percentage of malaria infection. These risk factors are associated with the three vertices of the HED theoretical framework. Religion and ethnicity show interesting directions that suggests future research.

Through this framework, I engage with the holistic complex human interactions with the environment. I note how humans carry around the diseased elements of the environment, infect others and then later re-infect themselves. I observe how socially constructed norms encourage humans to practise their culture and earn a living, and in these cases expose themselves to elements of disease, but without exposing their children. I note how heads of households hold multiple aetiologies on disease irrespective of their education, religion, and wealth. I observe how malaria varies with household size and density, and the presence of animals. Through it, I account for people's experiences of and struggles in using preventative measures (insecticide-treated mosquito nets, local herbs) in their homes, and how their lived experiences in their socio-culturally constructed places put them at risk. Through developing and exploring candidate models from the HED framework, I relate to Meade's (1977), Njama *et al.*'s (2003), Klinkenberg *et al.*'s (2006); Oppong and Harold's (2009) and Messina *et al.*'s (2011) explanation for the uneven distribution of malaria using this framework. I contribute theoretically by testing and applying this framework to provide a better understanding of the HED framework as well as for malaria within a human environment interaction.

This thesis contributes empirically through its main findings, which state that urban malaria patterns are not climatically induced and as such may be influenced by other non-climatic factors, as raised previously by Lafferty (2009). Through the application of the mixed-methodological approach, as stated earlier, I test these non-climatic and climatic variables to identify important variables for the study area. Narrowing down on these variables is an important empirical contribution from my research.

The product of my theoretical and methodological contributions and the heart of this thesis is a range of predictive models that express the complexity of the disease and its interaction with the environmental and socio-cultural characteristics of Lagos, Nigeria. The models show that socio-cultural risks and exposures put populations in locations of risk of the disease in ways that are their choice, or by design, and interact with the

attributes of that environment. Some of these exposures may not always arise from household locations, but from old or new types of occupation or ways of life where environmental conditions outside household locations may then need to be evaluated. Night life, which is a feature of urban areas, intersects with changing climate, human behaviours and new or additional occupations for households to deal with socio-economic commitments.

9.2.7 Public Engagement of the Study

In addition to the theoretical, methodological and empirical impact that this research makes, the investment of efforts in data collection led to the development of two spatial products that have positive public health implications. A spatio-temporal malaria information system (STEMIS), which did not previously exist, was created from aggregate malaria values and developed from scratch, and this was used to identify areas reporting elevated disease rates and investigate the malaria–climate relationship.

In addition, the household, environmental and malaria risks spatial database product overcomes the limitations of DHS data (e.g. coarse spatial scale, limited malaria information and lack of environmental data), which would have been impossible without the use of mixed methods emanating from this research effort. The availability of the household and malaria risk database allowed the investigation of environmental risks and the development of a predictive model that typifies the future urban ecology scenario in the African environment.

These databases provide a platform for public health decision-making. In particular, the spatio-temporal malaria information system (STEMIS) has been a point of engagement with LSMoH, who have acknowledged the current quality of their reporting and are making efforts to retrieve missing data from their source documentation. In its current state, they have also found it to be a foundation to explore spatial and temporal patterns of malaria in digital forms which they have never had previously.

On the wider impact of this study and its data contribution, as LSMoH have experienced the greater possibilities that archived data can have when held and applied in an accessible format, they have also considered ways to build the capacities of the private HCFs to gather and report data so as to measure appropriately the true burden of disease in the state. In addition, giving back to my research participants through the simple act of sharing research findings is helping the residents develop some experience with interviews and having some trust in individual researchers.

9.3 Future Research Directions

As a follow-up to this thesis, I have recommended a number of future studies to improve my research:

- I suggest an experimental study design to implement and assess some weak relationships in this study as well as integrate other variables such as drug resistance found in other studies to contribute to increased malaria.
- This research has successfully developed predictive models of urban malaria transmission that incorporate socio-cultural and environmental risk variables, as well as their interactions, using multivariate statistical approaches. However, future research should be undertaken to externally validate this model by using similar datasets, for which the second half of the household data, not employed in this research, may be useful.
- Future research should seek to employ data on daily malaria infection and meteorological variables to further test the association between these variables in time-lags that allow the modelling of the biological characteristics of the vector and parasite. It should also explore the use of autoregressive and dynamic models, to further re-assess and quantify the relationship between clinically diagnosed malaria and meteorological variables, and assess for seasonality to reconfirm the current findings on the relationship between meteorological variables and malaria infection.
- This research has focused on examining household environments, and one of the main findings is that working at night under conditions without mosquito protection puts adults not ordinarily at risk at higher risk in their workplace than in their homes. The public health implications of these findings suggest that future research should focus on examining working conditions and environments in order to separate risks at home from risks at work.
- Another suggestion for further research is the intersection of ethnicity, religion, place attachment to riverine areas and environmental risk, dressing and historical immunities. As the role of the ethnic groups in Lagos and religion is less understood, I suggest future research that focuses on deriving more conclusive evidence on its role in urban malaria. In doing so, this would contribute to policy that would be useful when targeting intervention appropriately.

9.4 Conclusion

This research set out to examine overall the ecology of urban malaria, through assessing the contributory influences of a broad range of environmental and socio-cultural risk variables on the disease in households in a predictive model of ecological origin which has not been sufficiently investigated. The thesis achieved this aim and its objectives in the study location of Lagos, Nigeria. Through the thesis I have created knowledge of this location from my field experiences and empirical research thereby engaging with the broader literature on development research as well as the sub-discipline of medical and health geography. I have also engaged with broader literature in geography such as the works of Jessop *et al.* (2008) and Jones and Woods (2013) that argue that localities are different and so will their needed solutions be different. Therefore promoting the study of new localities in order to create new knowledge that will contribute to policies and encourage development should be considered.

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Appendices

Appendix I: Urban Agriculture



Vegetable farming in Kosofe LGA



Animal Husbandry Activities in Kosofe LGA

Appendix II: Indigenous Homes in Riverine Communities in Lagos State



Riverine Communities in Kosofe LGA

Appendix III: Permission and Affiliation Letters, University of Lagos



School of Geography,
Politics and Sociology

5th Floor, Claremont Tower
Newcastle upon Tyne
NE1 7RU United Kingdom

Professor A E Gillespie
Head of School

18th February 2008

The HOD
Geography Department
University of Lagos,
Akoka, Lagos, Nigeria

Dear Sir,

Request for affiliation to Geography Department, University of Lagos, Nigeria

I am Anthonia Ijeoma Onyiahialam-Okoro and I graduated with my first degree and Msc in Geography/Planning, University of Lagos 1997 and 1999 respectively. I am presently a PhD student of Medical Geography under Dr Seraphim Albanides & Dr Eugene Sobngwi supervisions (s.alvanides@ncl.ac.uk; eugene.sobngwi@ncl.ac.uk) at Newcastle University, UK. My PhD research interests are in Health, Environment and Development specifically "The spatio temporal understanding of Malaria in the social and physical environment of Nigeria using Remote Sensing, GIS & Spatial statistics".

I will be undertaking my field work research in Nigeria (March to July 2008) and will like to seek affiliation with your department and my alma mater. This is to enable me undertake my data collection exercise properly within a Nigerian context and also share in the expertise of the department. I am also willing to be part of any relevant exercise in the Geography department during this period or any other time if called upon. I will also acknowledge the support of the Geography department, University of Lagos, Nigeria in my research work.

Further information can be obtained from my supervisors and my contact email address is a.i.onyiahialam@ncl.ac.uk

Thank you for your cooperation and I look forward to hearing from you.

Kind regards,

Anthonia Ijeoma Onyiahialam-Okoro

tel: +44 (0) 191 222 3923

fax: +44 (0) 191 222 5421

www.ncl.ac.uk/geps

The University of Newcastle upon Tyne trading as Newcastle University



UNIVERSITY OF LAGOS

FACULTY OF SOCIAL SCIENCES
DEPARTMENT OF GEOGRAPHY

Fax: +234 - 01- 822644

Your Ref:

Our Ref:

LAGOS NIGERIA

Tel: 01 - 826401

Telegrams: University Lagos.

Date:

21st February, 2008

Anthonia Ijoma Onyiahialam-Okoro
Graduate Student
School of Geography, Politics and Sociology
Newcastle University
Newcastle upon Tyne
United Kingdom

Dear Mrs. Onyiahialam-Okoro

**Re: REQUEST FOR AFFILIATION WITH THE DEPARTMENT OF GEOGRAPHY,
UNIVERSITY OF LAGOS**

Your letter of 18th February 2008 on the above subject refers. I wish to inform you that the Department of Geography University of Lagos will be willing to host you for the period of your data collection in Nigeria. The Department will also be willing to give you all the necessary assistance within our reach to enable you properly undertake the data collection exercise in the country for your thesis.

Wishing you all the best.

Dr. OLATUNJI BABATOLA
Ag. Head, Geography Department
University of Lagos



UNIVERSITY OF LAGOS

FACULTY OF SOCIAL SCIENCES
DEPARTMENT OF GEOGRAPHY

Fax. +234 - 01- 822644

Your Ref:

Our Ref:

7th April, 2008

LAGOS NIGERIA

Tel: 01 - 826401

Telegrams: University Lagos.

Date:

TO WHOM IT MAY CONCERN:

IDENTIFICATION AND REQUEST FOR SUPPORT FOR MRS. ANTHONIA IJEOMA ONYEAHALAM-OKORO

Mrs. Anthonia Ijeoma Onyehialam-Okoro is a Ph.D Student in Geography at the School of Geography, Politics and Sociology, Newcastle University, 5th Floor, Claremont Tower, Newcastle upon Tyne, United Kingdom. She is currently affiliated with the Department of Geography, University of Lagos for her fieldwork to collect the necessary data for her thesis in Nigeria.

Her Ph.D research interests are in Health, Environment and Development. Her research topic is "The spatio temporal understanding of Malaria in the social and physical environment of Nigeria using Remote Sensing, GIS & Spatial statistics".

I therefore request for your support and cooperation to enable her complete her fieldwork and data collection exercise on schedule.

Warm regards.

Dr. OLATUNJI BABATOLA
Ag. Head, Geography Department
University of Lagos

HEAD
GEOGRAPHY DEPARTMENT
UNIVERSITY OF LAGOS

Appendix IV: Permission and Ethical Clearance for Pilot Study Lagos State Ministry of Health



LAGOS STATE GOVERNMENT MINISTRY OF HEALTH

Block 4
The Secretariat,
Alausa, Ikeja.
P.M.B 21007, Ikeja.

Tel/Fax No. 234-1-1-4969061
Website: www.lagosstateministryofhealth.org

LSMOH/HMIS/III/97

May 15th 2008

Ref. No:

Date:

Dear Mrs Anthonia I. Onyehialam-Okoro,

Re: Request for Permission to Undertake Data gathering for PhD study on Malaria in Lagos State

With reference to the above, this is to inform you that your request for permission to undertake your research titled "Spatio-Temporal Understanding of Malaria Persistence" in Lagos State has been approved. The study will be conducted as part of the Eko Free Malaria Program for Lagos State and you will work with the project staff. Please note that the program already has ethical clearance.

It is expected that you shall share your findings and feedback with the relevant departments and support the program where necessary with your expertise.

Yours sincerely,

Dr. V.O. Omoera

Head: Health Management Information Systems (HMIS) Department

DUPLICATE

MISSION STATEMENT: "To deliver qualitative, affordable and equitable healthcare services to the citizenry applying appropriate technology by a highly motivated staff"

Appendix V: Fieldwork in Ikeja and Kosofe LGAs



Recruiting participants in Ikeja and Kosofe LGAs

Appendix VI: Semi-structured Interview Protocol



Introduction and Consent for Interview

For interviewers use only

Greetings, My name is Mrs Anthonia I. Onyehialam-Okoro a PhD student at Newcastle University, UK. I am conducting research on malaria disease and the socio-cultural environment. I will like your support in my research work by responding to my questionnaire/ interview survey. The research is funded by Dorothy Hodgkins Post Graduate Award, UK.

The objectives of the research are:

1. To obtain information at household level on
 - Malaria
 - Working environments
 - Housing characteristics
 - Economic characteristics
 - Household characteristics
 - Behavioural, social and cultural characteristics

I will very much appreciate your participation in questionnaire/semi-structured interview which will take about 30 to 45 minutes. This information will support the achievement of a PhD that could also influence future malaria intervention policies. Whatever information you provide will be kept strictly confidential and will not be shown to other persons. At the end of the project you will receive a copy of the report in a format useable to you unless otherwise stated. Should you have any queries, please feel free to use the contacts below.

Anthonia Ijeoma Onyehialam Email: a.i.onyehialam@ncl.ac.uk

Telephone: +234-7086124580

Dr Eugene Sobngwi: eugene.sobngwi@ncl.ac.uk

I also like to let you know that participation in the interview is completely voluntary and targeted to respondents above 18 years of age and heads of households. If this applies to you and we should come to any question you don't want to answer, please let me know and I will proceed to the next question. You can also stop the interview at anytime should you wish to. However, since your views are important, we hope you will participate.

At this time, do you want to ask me anything about the interview?

Sir/Ma can I confirm if you are above 18 years of age and you are a head of household? Yes/No

Do you have a preference for written or verbal consent? (Mark choice, signature required for written consent)

1. Written consent.....
2. Verbal consent.....

May I begin the interview now?

Give one copy of the information page to respondent

Ask about the head of household or otherwise, Introduce self and research and solicit support towards the interview

1. Can you remember a time in the life of your household when someone had malaria? (Tell me about that. How did you respond to it?)
2. Are there situations when you were not sure it was malaria? (Why? How did you confirm this? Where there signs, symptoms, causes you were familiar with?)
3. In Nigeria, we know that power situation can often be a challenge. How do you manage this? Do you sleep with your windows/doors open? Do your household members spend time outside in the evening/ night?
4. When you think through your daily schedule and that of your household, are there activities that gives you concerns for mosquito bites? Tell me about it.
5. How do you protect yourself and your household members from having malaria?"
6. What is your treatment schedule like? Tell me what influences the treatment types you or any one in your household take for malaria?

Thank you for your time.

Please can you provide your contact details for further correspondence?

.....

Appendix VII: Demographic Characteristics of Interview Participants

Age Group (years)	No of Participants
18 to 30	7
31 -40	7
41-50	3
51 and above	1

Occupation	No of Participants
Professional	5
Semi-Professional	3
Non-Professional	7
Unemployed	1
Student	2

Gender	No of Participants
Male	12
Female	6

Location	No of Participants
Kosofe	10
Ikeja	8

Educational Qualification	No of Participants
Postgraduate degree	2
BSc	5
Diploma	4
Senior Secondary School Certificate	3
Junior Secondary School	1
Primary School	2
None	1

Marital Status	No of Participants
Single	5
Married	9
Widowed	2
Separated/Divorced	2

Ethnicity	No of Participants
Yoruba	7
Igbo	4
Hausa	2
Others	5



Anthonia Ijeoma Onyiahialam
PhD Research Candidate
Geography, Politics and Sociology
Newcastle University, UK
Telephone: +234-7086124580

Confidential Questionnaire for Academic
Research Purposes

Interviewer Details

Questionnaire No: 2008/AIO/PhD/Pilot/

Name of Interviewer:

Telephone number:

Date of Interview:

Questionnaire ID:

Interviewer Instructions

1. Please all questionnaires must be administered at the place of residence of respondents. Do not interview people at their place of work.
2. Please seek prior permission, show respect and obey cultural values within safety limits and where impossible discontinue survey and leave peacefully.
3. Please keep safe, avoid as much as possible entering into people's houses. Especially ladies.
4. Always move around with your ID cards and introduction letters

Introduction and Consent for questionnaire/ interview survey

For interviewers use only

Greetings, My name is _____, do you live here? I am helping Anthonia Ijeoma Onyiahialam in administering questionnaires/interviews for her PhD research work on malaria disease and the social and physical environment. The objectives of the research are: **(Move to No 1 and continue)**

For PhD researcher use only

Greetings, My name is Mrs Anthonia I. Onyiahialam a PhD student at Newcastle University, UK. I am conducting research on malaria disease and the social environment. I will like your support in my research work by responding to my questionnaire/ interview survey. The research is funded by Dorothy Hodgkins Post Graduate Award UK

1. To obtain information at household level on
 - Malaria
 - Working environments
 - Housing and its environment characteristics
 - Economic characteristics
 - Household characteristics
 - Behavioural, social and cultural characteristics

I will very much appreciate your participation in questionnaire/semi-structured interview. This information will support the achievement of a PhD that could also influence future malaria intervention policies. Whatever information you provide will be kept strictly confidential and will not be shown to other persons. At the end of the project you will receive a copy of the report in a format useable to you unless otherwise stated. Should you have any queries, please feel free to use the contacts below.

Anthonia Ijeoma Onyiahialam Email: a.i.onyiahialam@ncl.ac.uk

Telephone: +234-7086124580

Dr Eugene Sobngwi: eugene.sobngwi@ncl.ac.uk

I also like to let you know that participation in the survey is completely voluntary and targeted to respondents above 18 years of age and heads of households. If this applies to you and we should come to any question you don't want to answer, please let me know and I will proceed to the next question. You can also stop the interview at anytime should you wish to. However, since your views are important, we hope you will participate.

At this time, do you want to ask me anything about the survey?

Sir/Ma can I confirm if you are above 18 years of age and you are a head of household? Yes/No

Do you have a preference for written or verbal consent? (Mark choice, signature required for written consent)

1. Written consent.....
2. Verbal consent.....

May I let you know that as part of the incentive, at the end of the study you will receive a feedback report unless you state otherwise.

May I begin the interview now?

After each question, I will read out the answers and you can choose the most appropriate.

Give one copy of the information page to respondent

Questionnaire survey

Please tick the appropriate answers in the boxes beside the questions and where open ended questions are asked write down the answers exactly

MALARIA

At what time of the year do you or members of your household experience malaria most frequently?
Please let respondent choose most suitable timelines that can be remembered.

January	
February	
March	
April	
May	
June	
July	
August	
September	
October	
November	
December	

New Year	
Christmas	
Easter	
Long vacation	
Others (specify)	

Dry season	
Wet season	

Comment box

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

Which of the following do you think cause malaria? Tick as many as the respondent thinks.

	Yes	No	Not sure/Don't know
Mosquito bites			
Sleeping outside			
Touching a person with malaria			
Staying under the sun or near heat or fire			
Eating oily and fatty food			
Dirty environment			
Eating unripe or overripe fruits like mangoes, paw paw etc			
Not eating well			
Constipation			
Eating food touched by houseflies			
Breastfeeding a baby			
Drinking too much alcohol			
Others (specify)			

Are there any others you can think about that cause malaria?

Do you have any pregnant household member?

1. Yes
2. No
3. Others (specify)

Which of the following signs do you think is associated with malaria or any serious case of malaria symptoms?

Tick as many as the respondent thinks

	Y	N	I don't know/Not sure
Fever or continuous high fever	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Headaches and persistent headaches	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Aches and pains	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
High temperatures	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Loss of appetite	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Dizziness	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Shivering	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Mouth bitterness	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Vomiting	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Cough	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Convulsion	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Anaemia	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Yellowness	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Diarrhoea	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Are there any others you can think about that is associated with malaria ?

How often per (week/month/year/others (specify)) do the following age grouped members of the household have malaria? **Please specify timeline**

Age	frequency	Time period
0 to 4		Week/month/years/others
5 to 14		Week/month/years/others
14 to 19		Week/month/years/others
20 to 49		Week/month/years/others
≥50 years		Week/month/years/others

HEALTH CARE ACCESS

If you use a health facility which one do you and household members use?

PUBLIC SECTOR

1. Government hospital
2. Other government (please specify)

PRIVATE MEDICAL SECTOR

1. Private hospital or clinic
2. Pharmacy
3. Chemist/patent medicine store
4. Private doctor
5. Mobile clinic
6. Field worker
7. Other private (please specify)

OTHER SOURCE

1. Shop
2. Traditional healer
3. Church
4. Others (please specify)

Which health facility do you use? Please specify name and location.....

.....

If you use a health care facility, in average how much it costs you to treat malaria at every instance (**This includes costs of drugs, tests, and consultancy charges**)

1. Less than 300 naira
2. 301 to 600 naira
3. 601 to 900 naira
4. 901 to 1200 naira
5. Greater than 1200 naira

Comments

	Y	N	Questions
Asked for clarification	<input type="checkbox"/>	<input type="checkbox"/>	
Required further probing	<input type="checkbox"/>	<input type="checkbox"/>	
Question difficulty for interviewer	<input type="checkbox"/>	<input type="checkbox"/>	
Others	<input type="checkbox"/>	<input type="checkbox"/>	

What about in the past?

1. Yes
2. No
3. Others (specify)

If any member of your household is pregnant or has been pregnant previously, in what ways does she prevent or treat malaria? Please list

1. No one has been pregnant
2. Others (please specify)

Does your household have any mosquito net that can be used while sleeping?

1. Yes
2. No
3. Others (specify)

How many mosquito nets does your household have?

Who sleeps under the mosquito net in the household?

Was the mosquito net used last night?

1. Yes
2. No
3. Others (please specify)

Have you or anyone in your household had malaria in the last year?

If yes, how was it treated?

What about malaria in the last month?

.....

If yes, how was it treated?

COMMENTS:

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

HOUSING CHARACTERISTICS

What is the size of your household presently occupying this home?

.....

What type of accommodation do you live in?

1. Shared facility
2. Self contained
3. Face me I face you
4. Chalet
5. Flat
6. House
7. Others (please specify)

How many rooms in total are in your household including rooms for sleeping and other rooms?

How many rooms are used for sleeping in your household?

How many sleeping beds have you in your household?

Which of the following are you to this accommodation?

1. Owner
2. Owner's representative/caretaker
3. Family ownership i.e. is living rent free
4. Renter/tenant
5. Others (please specify)

How long have you lived in this accommodation?

1. Less than one year
2. One to three years
3. Four years to six years
4. Seven years to nine years
5. Ten years and above

How long ago have you being using the health care facility?

1. < 2 years
2. 2 years plus to 4 years
3. 4 years plus to 6 years
4. > 6 years

What transport type do you normally use to visit the health care facility?

1. Walking
2. Public transport
3. Own vehicle
4. Someone's vehicle
5. Others (pls specify)

For how long do you need to travel to reach the health facility?

1. < 10 minutes
2. 10 minutes to 20 minutes
3. 20 minutes to 30 minutes
4. 31 minutes to 1 hour
5. > 1 hour

If you use public transport how many connections do you need to make to reach the health care facility?

1. None
2. One
3. Two
4. Three
5. Greater than three

COMMENTS:

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

Which of the following mosquito protection do you have at home?

1. Windows net
2. Door net
3. Others (specify)

What is the condition of the mosquito protection?

1. Major tears
2. Minor tears
3. None
4. Others (specify)

Does this household own any pets, livestock, herds or other household animals kept in the compound/yard/flat?

1. Yes
2. No
3. Others (specify)

Do you have any farm or gardens or bushes around in the compound/flat/yard?

1. Yes
2. No
3. Others (please specify)

Which of the water sources do you use in the household?

1. Piped water into house
2. Piped water to ward/plot/compound/Public taps/Standpipe
3. Drawn well or borehole
4. Purchased water from tanker truck
5. Cart with small tank
6. Surface water (River/Dam/Lake/Pond/Stream/Canal/Irrigation channel)
7. Others (please specify)

What materials are used for building walls?

1. No walls
2. Cement
3. Bricks
4. Mud/Earth/Laterite
5. Raffia/Leaves
6. Wood
7. Cardboard
8. Stone
9. Others (please specify)

What is the condition of the building walls?

1. No cracks
2. Minor cracks
3. Major cracks
4. Others (please specify)

What materials are used for building roofs?

1. Corrugated metal sheets
2. Tiles
3. Asbestos
4. Zinc
5. Aluminium long span
6. Concrete slabs
7. Others (specify)

What is the condition of the building roofs?

1. No evident leaks
2. Leaks evident
3. Others (specify)

What is the condition of the building roof?

1. Complete
2. Incomplete
3. Others (specify)

COMMENTS:

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

How much do spend on the following? Use most useful period and specify it)

Item	Amount	Period
Rent		D/W/M/Y/O
Feeding		D/W/M/Y/O
Transport		D/W/M/Y/O
School fees		D/W/M/Y/O
Medicals		D/W/M/Y/O
Religion		D/W/M/Y/O
Social		D/W/M/Y/O
Funeral		D/W/M/Y/O
Others (specify)		D/W/M/Y/O

If you estimate what your income has been in the last 10 years?

	Higher	Same	Lower
Was it lower or higher 3 years ago than presently?			
Was it lower or higher 6 years ago than presently?			
Was it lower or higher 9 years ago than presently?			
Was it lower or higher 10 years ago than presently?			

Do you store water in the house?

1. Yes
2. No
3. Others (please specify)

What type of toilet facility do members of your household usually use?

1. Flush toilet
2. Pour flush toilet
3. Pit latrine
4. Composting toilet
5. No toilet facility/bush/field
6. Others (please specify)

Do you share toilet with other household?

1. Yes
2. No
3. Others (specify)

How many households use this toilet facility?

ECONOMIC CHARACTERISTICS

In order to assess income levels we need to know about income. Would you please tell me how much money comes into this household for each relevant period from every member?

How much in wages		D/W/M/Y/O
How much in business profit?		
How much in rents		
How much in regular gifts		
How much in dash		
Others (please specify)		
Total (leave blank)		

COMMENTS:

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

Does any member of your household own any land or landed property?

1. Yes
2. No
3. Others (please specify)

If yes, how many?

Land		Per acre/plot/hectare
Other property		Per acre/plot/hectare

Does any member of your household own any of the following items in good working order?

	Yes	No
Radio/Cassette/DVD player		
Sewing machine		
Bicycle		
Refrigerator		
Deep freezer		
Television		
Okada		
Car/taxi/van/truck		
Generator		
Grinder		
Computer/laptop		
Sleeping beds		
Cable TV/DsTV		
Air conditioner		
Bank account		

HOUSEHOLD SOCIO- DEMOGRAPHIC

How old are you?

How many people fall within this age range in your household?

1. 0 to 4 years
2. 5 to 14 years
3. 14 to 19 years
4. 20 to 49 years
5. 50 years and above

What is your native language?

1. Hausa
2. Yoruba
3. Igbo
4. Others (please specify)

Please indicate your gender?

1. Male
2. Female
3. Others (specify)

What is your marital status?

1. Single
2. Married
3. Divorced
4. Living together
5. Widowed
6. Others (please specify)

How many years of altogether of education did you complete?

What is your level of education?

1. None
2. Primary school
3. Secondary school
4. Higher education
5. Others (please specify)

What is the highest (class/form/year) reached at the completed years?

If you have a spouse how many years of completed education does he/she have?

What is your primary occupation? Please state

What type of job do you presently do?

In a couple who has the greater say in each of the following decisions?

	Hus-band	Wife	Both equally	Don't know/depends	N/A
Deciding what malaria treatment will be taken					
Deciding how finances will be managed					

COMMENTS:

	Y	N	Questions
Asked for clarification			
Required further probing			
Question difficulty for interviewer			
Others			

Appendix IX: Pilot Study Results

Introduction

We conducted a pilot study between March and June 2008, to administer an interviewer-led questionnaire in survey in 51 households and a semi-structured interview with 18 participants all residing in the Ikeja and Kosofe local government areas of Lagos state. This was part of the process of developing and testing a questionnaire to administer in a larger study as well as generate qualitative information on households, in order to achieve the greater goal of examining the environmental and socio-cultural risks of households to urban malaria.

We summarise this interim result from the pilot study, describing the themes that emanate from the semi-structured interview and the details of the questionnaire survey.

Semi-structured Interviews

Behaviours

Two themes and trends in behaviours were identified through the semi-structured interviews conducted. The preventative behaviours leading or protecting from human vector contact and disease, and the treatment-seeking behaviours as they influenced the types of treatments employed.

Treatment-seeking Behaviours

Treatment-seeking behaviours have implication for the development of severe malaria. According to the interview results presented in the next table, key terms associated with home treatment-seeking included buying orthodox medication and the use of non-orthodox herbal treatments locally known as “*agbo*”. This was the households’ first choice of treatment for malaria. *Agbo* is a traditional herbal treatment made from the liquid extracted from boiled medicinal leaves. It is a commonly used as a preventative and treatment option for many illnesses amongst the local tribes like the Yorubas. It is claimed to provide good health and can minimise the severity of any illness if taken on a daily basis. The herbs can be taken orally, used in a bath or a soak. Due to its commonness, it is hawked by road sellers and can also be home-made. According to the survey, over 80% of the participants did not first go to an HCF at the onset of malaria symptoms. They relied on home treatment, with some participants using a combination of orthodox and non-orthodox treatments. The first choices of treatment cut across the

different economic classes though participants that belonged to the medium- and high-income classes accounted for the majority choosing the use of an HCF.

Reports on treatment seeking behaviour (TSB) from participants revealed differing experiences from different economic classes. PT6,said,

“... depending on how much I have, I take tablets like paracetamol and when I have more money I will ask the chemist to give me vitamins and other food supplements. I don’t go to hospital, I have never considered it. I take members of my household to the chemist anytime they are ill. We also take agbo and for my wife, when she is pregnant it is a must.”

(Male, 45 years old)

PT6 followed up by saying that

“If I don’t have money I will ask the person in the shop to remove some medicine, for example to the tune of 250 naira (£1) if that is what I have at that time.”

(Male, 45 years old)

Summary of Choice of First Treatment Options

Key terms	Frequency of occurrence	Percentage
Buy medication for home treatment	37	76
Take herbal treatment like “agbo”	4	8
Visit the clinic immediately	4	8
Conduct a lab test	3	6
Prayer	1	2
No malaria ever experienced	1	2
Combination of orthodox and non-orthodox treatment	3	6

Another participant PT1 of medium-level status reported the use of paracetamol as the first option and, when it did not get better, she took malaria tablets like fansidar. However, she mentioned that all members of her household hardly have malaria because they use mosquito net.

PT2, from a high-income status reported he had never suffered malaria. He said

“... Malaria ke? I have never had malaria in my life. Everyone in my household is well protected and my father is a medical doctor as well as my sister and so they are normally careful so we don’t have the disease. So I have never heard anyone talk about malaria in my life and I am 31 years now.”

(Male, 31 years old)

Some participants revealed that they take other treatment types when the first choice of orthodox treatment fails. Other combinations of treatment used are seeking medical treatment from health care facilities, using a nurse, taking herbal treatment like *agbo*, using balm, prayers, hot tea and church. Approximately half of the participants that take medications as their first treatment choice also consider the use of herbal treatment while the other half considered visiting a health care facility for further treatment. PT7 said that, apart from using home treatment like medicines purchased from chemists and pharmacies, he did not take herbal treatment like *agbo*. In his words,

“I do not trust herbs because they don’t have any dosage, you don’t know the constituents or their concentration levels. One would never know when you overtake or undertake the mixture. I had a bad experience with it because I took it without knowing dosage and for weeks I was seeing double, I wasn’t myself and since then I said never again. I also don’t go to hospital, I use a nurse who buys the necessary treatment and comes to my house to treat us. She treats us better than the hospital because she is focusing only on us and there is no need for queues. I pay as high as N7,000 (~£28), much more than the health care. She gives us medicines, drips where necessary. She is very experienced.”

(Male, 39 years old)

PT8 another participant reported that her first choice for malaria treatment depends on who it is. She reports taking members of her household to the healthcare facility in the event of malaria, but treating herself using herbal medicines like *agbo*. PT8 reports that she feared taking orthodox medicine and didn’t know how to take it because always mixed them up. There were other participants who used a combination of treatment options like malaria medicines, pain relievers and herbs (*agbo*). Some participants who took home treatment first sought advice from the chemist and pharmacies where the drugs were purchased.

Determinants of First Treatment Choice

Various factors and combinations of factors have been reported to influence treatment choice in households. The main determinants are the severity of the illness and finance, followed by distance/nearness of health care facility. The table below shows a breakdown of how often these key terms occurred in the survey.

Determinants of Treatment Choice

<i>Key terms</i>	<i>Frequency of occurrence</i>
Intensity and severity of illness	25
Affordability	24
Physical accessibility	10
No consideration	6

Some of the main factors that influenced treatment-seeking behaviours (TSBs) identified from the interviews are presented in the table above and include the intensity of malaria, affordability and access, with some participants not giving a thought about it and always choosing home treatment first, because malaria is a simple disease. Affordability and intensity of illness have occurred most often and giving an indication of the role which knowledge and economic status can have in the risks of developing severe malaria. Some participants said that the ability of the patient to describe the symptoms and how they perceive the severity of the disease can be a determining factor for treatment types taken. For example when the illness is severe, they choose hospital-based treatment, otherwise they use home treatment. Severe malaria is associated with the *P. falciparum* parasite and accounts for the majority of deaths in vulnerable populations. The ability to seek prompt hospital treatment for severe forms of malaria is reported as the key to reducing deaths associated with it. However seeking adequate treatment can be marred by knowledge, affordability and even physical access where these have occurred in same populations that have developed severe forms of the illness. As PT6 earlier echoed,

“If I don’t have money he will ask the person in the shop to remove some medicine for example to the tune of 250 naira (~£1) if that is what I have.”

(Male, 45 years old)

The availability of funds can determine the kind of medication that some participants request from a health care facility or pharmacy/chemist. These narratives reveal the extent to which people depend on home treatment for malaria and the various factors that influence the choices. The treatment-seeking behaviours observed from the interview have shown that routinely reported malaria data from HCFs cannot be relied upon to represent the true state of the population infection level. They are therefore likely to reflect occurrence of severe malaria and not mild or unconfirmed cases.

Preventative and Risky Behaviours

Preventative behaviours can reduce human vector contact eliminating mosquito bites and minimising the occurrence of malaria. Risky behaviours, on the other hand, can expose people to increased human vector contact and increased occurrence of disease. They are classified as risky behaviours and habits that put humans at risk of diseases and preventative actions targeted to reduce the occurrence of malaria.

Key terms arising from the interview that are associated with preventative behaviours are use of door nets, windows nets, mosquito nets (treated and untreated), insecticide sprays, fleet, anti-malarial tablets, *agbo*, fumigation, mosquito coils. There was high usage of window nets followed by door nets and insecticide sprays as against the use of bed nets according to the table below. Participants reported limited use of bed nets even with the promotion and distribution during intervention programs. Responses given were

“I don’t use bed nets because I feel very hot in the night and there is no electricity to use the fan.”

PT7 reported that bed nets were not used due to not having suitable sleeping places. An excerpt of his narration says,

“Bed nets? Where will I fit them, with some of my people sleeping on the chair or floor. I don’t even use window nets otherwise we will suffocate. I use Otapiapia.

(Male, 39 years old)

Otapiapia is a locally made insecticide that is commonly used to eliminate the presence of insects and pests including mosquitoes.

Protective Practice for Malaria

<i>Key terms</i>	<i>Frequency of occurrence</i>
Insecticide and mosquito spray	28
Bed nets	14
Window nets	35
Door nets	29
Preventative medication	6
Mosquito coils	6

Though the majority of participants reported not being involved in any risky behaviour that purposely put them at risks of mosquito bites, some habits which appeared

unintentional were noted. They included opening the door and windows at night to allow fresh air due to poor ventilation and lack of electricity to power fans, the way they spent their evenings and nights. Some of the participants that had the habit of leaving their door and windows open in the evening and nights and the reason given was attributed to poor ventilation and lack of electricity to power fans. Other habits of participants included their social lifestyles and occupations that necessitated them to spend the evening and nights outdoors without using any preventative measures. PT7, one of the participants, said,

“It is in the night from 7pm to 3am I make my money and I am not thinking about mosquitoes. Bachelors or others who want to have good time after work come and eat at my table. I need to put my table outside so that they can hear my music and call on friends passing by. Also there is no electricity for fan even if they want to stay inside. I used to use mosquito coil but my customers complain of the smell so I stopped.”

(Male, 39 years old)

These statements show that apart from household residential risks for malaria, there could be social and occupational risks associated with the disease in urban areas which most studies have not accounted for.

Belief

The issue of belief arose while interviewing people about their knowledge of malaria causes, identification and systems. There was a general agreement on the cause of malaria to be from mosquitoes. However there appeared that there was the existence of belief issues with participants across economic, ethnicity and religion classes. All participants reported some form of belief by reporting other causes of malaria such as heat and staying under the sun, transfer of malaria from mother to baby during breastfeeding, PT6, one of the participants reported that his wife took *agbo* while she was pregnant so that if she had malaria it would not be transferred to the baby. He emphasised the importance of *agbo* during pregnancy as a strong preventative treatment for mother–child transfer of disease.

These reports from the interview present behavioural and cultural aspects of malaria risks in households and these contributed to the development and improvement of the questionnaire administered in the main survey. The feedback from the interviewer-administered questionnaire discussed economic characteristics of participants and their reactions. This is presented next.

Questionnaire Survey

In the pilot survey an interviewer-administered questionnaire elicited information on a range of social characteristics. Here, the economic level index classes, response rates and reactions to potentially difficult questions, which are associated with economic characteristics information, are discussed. Forty-nine participants, representing 96% of the sampled population of 51 responded to the piloted questionnaire survey.

Economic Characteristics

Economic characteristics were assessed by multiple approaches, income, expenditure and assets. This is to test and compare efficiency and usability in the study area, especially where income has been reported as the most theoretical indicator of choice (Rutstein and Johnson, 2004). The most successful of these approaches is the asset-based approach as used by Filmer and Pritchett (2001). Better access was recorded in interviewing low- and medium-income classes compared with the high-income class. It was difficult to access the high-income class because of security issues surrounding their homes. Participants of high economic status represented only 16.3% of the sample size, while low- and medium-income participants represented over 40% each of the sampled population of 49. In deriving the economic classes or wealth index, housing characteristics were not included even though this was used by Filmer and Pritchett (2001). This is due to the large number of participants who did not respond positively to the questions. Three economic classes, as per Filmer and Pritchett's (2001) approach, were derived and classed into the low-, medium- and high-income groups in 40%, 40% and 20% respectively, counting from the lowest asset value and ascending. The final classes are presented in the table below.

Economic Status of Households in Questionnaire Survey

		<i>Frequency</i>	<i>Percentage</i>
Economic classes	High	8	16.32
	Low	20	40.81
	Medium	21	42.85
	Total	49	100.00

The participants within the economic classes above provided the answers to the questionnaire survey. Though they responded more favourably to questions on assets, their responses to their income and expenditure approach were not as forthcoming.

Willingness to Respond

The results of the effort presented a poor result in terms of use of expenditure and income, compared to the use of an asset-based approach, Expenditure and income, rent and ownership of land and property were difficult to measure and the results of the attempt are presented in the next table.

According to the table below, there was a reluctance to give out information on rent; this varied according to economic class, with 32.7% of participants refusing to give out information on their rents. In terms of income, over 67.3% of participants refused to give information on their incomes, with the high-income earners accounting for about 13%. In the same table, there was a 33% non-disclosure rate regarding land and property ownership. The results of this analysis reflected that the income and expenditure approach was not a feasible option in this research even though it had been reported as an indicator of choice. Some of the reasons from the fieldwork report that led to the lack of disclosure for items such as rent or income were associated with the inability of some of the participants to calculate actual incomes and the uncertainty about whom the interviewers represented. Such reasons have also been reported by Rutstein and Johnson (2004) though Onwujekwe *et al.* (2010) have used it successfully in South-East Nigeria. The uncertainty in the use of income and expenditure approaches, as well as housing characteristics, led to the adoption of the asset-based approach and the inclusion of other assets locally suitable for the study.

Non-Response rates on different items

<i>Items</i>	<i>Percentage</i>
Response rate on rent	32.7
Response rate on income	67.3
Response rate on land and property ownership	33
Response rate on asset ownership	30

Information concerning houses, such as living conditions and homestead characteristics which elicited questions like “*What is the condition of your wall?*”, “*What is the condition of your roof?*” were not favourably responded to in the questionnaire survey. They were the difficult questions participants found very embarrassing to give a proper response. Some of their reactions such as “*why are you asking me about my wall, can you not see it? What is the relevance?*” showed lack of acceptance and unwillingness. In some instances desirability biases were setting in. Some may have been intentional

while some may not, as participants may not have understood the strict adherence to quality we were following in assessing these conditions. In order to maintain validity and reliability of the questionnaire, this information was used in developing a direct observation approach. This was used in a non-obstructive manner during the main study to gather information on homestead characteristics.

Appendix X: Barriers and Accessibility Issues in High Economic Households



Appendix XI: Malaria Infection Data Collection Template (2000 to 2002)

OUT – PATIENT/INPATIENT

Year:

Month:

Name of Health Facility:

Level:

Address/Location:

	Malaria Cases		Mortality from Malaria		Fever Cases		Total attendance @ health facility	
Gender	M	F	M	F	M	F	M	F
Number								

OUT – PATIENT/INPATIENT

Year:

Month:

Name of Health Facility:

Level:

Address/Location:

	Malaria Cases		Mortality from Malaria		Fever Cases		Total attendance @ health facility	
Gender	M	F	M	F	M	F	M	F
Number								

OUT – PATIENT/INPATIENT

Year:

Name of Health Facility:

Address/Location:

	Malaria Cases		Mortality from Malaria		Fever Cases	
Gender	M	F	M	F	M	F
Number						

Appendix XII: Malaria Infection Data Collection Template (2003 to 2009)

OUT - PATIENT/INPATIENT (CIRCLE AS APPROPRIATE)

Year:

Month:

Name of Health Facility:

Level:

Address

Local Government Area

Cost of Malaria laboratory tests

Range of costs for treating malaria

Disease	No of Malaria Cases by Age group												
	< 1 year		1-4yrs		5-14 yrs		15-49yrs		> 50 yrs		Total		Preg
Malaria Types	M	F	M	F	M	F	M	F	M	F	M	F	
Plasmodium Falciparum													
Plasmodium Vivax													
Plasmodium Malariae													
Plasmodium Ovale													
Cerebral Malaria													

	Total Attendances at Health Facility irrespective illness											
	< 1 year		1-4yrs		5-14 yrs		15-49yrs		> 50 yrs		Total	
Gender	M	F	M	F	M	F	M	F	M	F	M	F
Total Number of Malaria Laboratory Test												
	< 1 year		1-4yrs		5-14 yrs		15-49yrs		> 50 yrs		Total	
Gender	M	F	M	F	M	F	M	F	M	F	M	F

Appendix XIII: Interview Questions and Tasks for the System Assessment Protocol

	<i>Functional Areas</i>		<i>Summary Questions</i>	<i>Quality Dimension</i>
I	Data Source, Collection and Reporting Forms and Tools	1	Has the LSMoH identified a standard source document to be used by all Service Delivery Services (SDSs) to record the outcome of malaria? What is the connection between malaria treatment delivery and completion of the source document to record that service?	Reliability, consistency
		2	Has the LSMoH identified a standard rep reporting forms to be used by all SDS?	Reliability, consistency
		3	Do all SDS use the same source document and reporting form?	Reliability, consistency
		4	Is data recorded with sufficient precision/detail to measure specified malaria indicator?	Precision
II	Data Management Processes	5	Are challenges to data quality identified?	Reliability
		6	How are reported data stored? Is there an archiving system? Is there computer storage in place? In what format? Are they accessible for present or future use?	Accessibility, Availability
		7	Are data maintained in accordance with international or national confidentiality guidelines for patients and their personal data?	Confidentiality
III	Data-reporting system and their linkages	8	What are the avenues/units that collect and report data?	Reliability, consistency
		9	Does the data collection and reporting system of the health facilities and units' link to the State Reporting System? Is the data reporting duplicated?	Reliability, consistency
		10	Does the reporting system avoid double counting of patients? In each SDS, across SDS and identify drop-outs, dead patients, relocated patients etc	Accuracy and double counting
		11	How early is malaria indicator data report expected? Do SDSs keep to same timeliness? How is timeliness issues addressed?	Timeliness

Appendix XIV: Interview Questions and Tasks for Data Verification Protocol

	<i>Description of Tasks</i>	<i>Quality Dimension</i>
I	What are the connections between the completion of the source document, collection and reporting of data in the Lagos State system.	Reliability
II	Review and quantify availability, completeness of all indicator reported data for the selected reporting period.	Completeness
III	Trace and verify internal consistency of reported numbers: (1) Recount the reported numbers from available reports at SDS (2) Compare the results between SDS and reporting unit.	Accuracy
IV	Perform “cross-checks” of the verified report totals with other data sources to assess reliability and consistency (e.g. laboratory reports, registers, etc.).	Reliability

Appendix XV: Ethical Clearance for Main Study, Federal Ministry of Health, Nigeria



National Health Research Ethics Committee of Nigeria (NHREC)

Promoting Highest Ethical and Scientific Standards for Health Research in Nigeria



Federal Ministry of Health

NHREC Protocol Number NHREC/01/01/2007-11/10/2010

NHREC Approval Number NHREC/01/01/2007-22/10/2010

Date: October 26, 2010

Re: Spatio Temporal Analytical Approach to the understanding of Malaria Persistence in the Social and Physical Environment of Lagos Communities and its data quality assessment.

Health Research Ethics Committee (HREC) assigned number: NHREC/01/01/2007

Name of Principal Investigator: Ms. Anthonia Ijeoma Onyiahialam

Address of Principal Investigator: University of Newcastle

Newcastle Upon Tyne, UK

e-mail: a.i.onyiahialam@ncl.ac.uk

Date of receipt of valid application: 11-10-2010

Date when final determination of research was made: 22-10-2010

Notice of Full Committee Approval

This is to inform you that the research described in the submitted protocol, the consent forms, advertisements and other participant information materials have been reviewed and given full committee approval by the National Health Research Ethics Committee.

This approval dates from 22/10/2010 to 21/10/2011. If there is delay in starting the research, please inform the HREC so that the dates of approval can be adjusted accordingly. Note that no participant accrual or activity related to this research may be conducted outside of these dates. All informed consent forms used in this study must carry the HREC assigned number and duration of HREC approval of the study. In multiyear research, endeavor to submit your annual report to the HREC early in order to obtain renewal of your approval and avoid disruption of your research.

The National Code for Health Research Ethics requires you to comply with all institutional guidelines, rules and regulations and with the tenets of the Code including ensuring that all adverse events are reported promptly to the HREC. No changes are permitted in the research without prior approval by the HREC except in circumstances outlined in the Code. The HREC reserves the right to conduct compliance visit your research site without previous notification.

Signed

Clement Adebamowo BMChB Hons (Jos), FWACS, FACS, DSc (Harvard)

Honorary Consultant Surgeon, Director, West African Center for Bioethics and

Chairman, National Health Research Ethics Committee of Nigeria (NHREC)

Department of Health Planning, Research & Statistics
Federal Ministry of Health
11th Floor Federal Secretariat Complex Phase III
Akinolu Bello Way, Abuja

Tel: +234-09-523-6067
E-mail: chairman@nhrec.net, secretary@nhrec.net,
deskoffice@nhrec.net,
URL: <http://www.nhrec.net>

Appendix XVI: Ethical Clearance for Main Study, Newcastle University, UK



Faculty of Humanities and Social
Sciences

Newcastle University
7th floor, Daysh Building
Newcastle upon Tyne
NE1 7RU United Kingdom

30th September 2010

Anthonia Ijeoma Onyiahialam
Postgraduate Student
School of Geography, Politics & Sociology
Newcastle University

Dear Anthonia,

Thank you for your application to the HaSS Ethics Committee for approval of your project entitled "Spatio Temporal Understanding of the Persistence of Malaria in the Social and Physical Environment of Lagos Communities". I am pleased to confirm that Gerry Docherty is happy to approve your application on behalf of the Committee.

Yours sincerely

A handwritten signature in black ink that reads "Wendy Davison".

Mrs Wendy Davison
Secretary to Gerry Docherty,
Lorna Taylor and Sue Mitchell
Faculty of Humanities and Social Sciences
Daysh Building
Newcastle University
Newcastle upon Tyne
NE1 7RU

Telephone: 0191 222 6349
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fax: +44 (0) 191 2227001

www.ncl.ac.uk

The University of Newcastle upon Tyne and Newcastle University



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Newcastle upon Tyne and Newcastle University
2005

Appendix XVII: Direct Observation Protocol – Household Environment

Presence of:

	Yes	No
Bushes		
Grasses		
Garden		
Farmyard		
Flowers		
Trees		
Open drains		
Stagnant/standing water		
Refuse or garbage point		
Others		

Building walls

	Yes	No
Cracks		
Complete		
Others		

Roof

	Yes	No
Leaks evident		
Complete		
Others		

Mosquito protection: Windows

	Yes	No
Tears		
Others		

Mosquito protection: Doors

	Yes	No
Tears		
Others		

Appendix XVIII: Main Questionnaire Survey



Anthonia Ijeoma Onyeahialam

PhD Research Candidate

Geography, Politics and Sociology

Newcastle University, UK

Telephone: +234-7086124580

Confidential Questionnaire for Academic

Research Purposes

Questionnaire ID:

Interviewer Details

Questionnaire No: 2010/AIO/PhD/Main/
Initial

Interviewer and Questionnaire number

Name of Interviewer:

Telephone number

Date of Interview:

Start of Interview

End of interview

Interview complete: Yes/No

Respondent Details

Head of Household : Yes/No

Relationship to Head of Household

House Address:

GPS Coordinate

Type of Building:

Locality:

Interviewer Instructions: ENSURE YOU GATHER CONTACT INFORMATION

1. Please all questionnaires must be administered at the place of residence of respondents. Do not interview people at their place of work.
2. If respondent is illiterate please use pidgin English or Yoruba according to training instructions and questions
3. Please seek prior permission, show respect and obey cultural values within safety limits and where impossible discontinue survey and leave peacefully.
4. Please keep safe, avoid as much as possible entering into people's houses. Especially ladies.
5. Always move around with your ID cards and introduction letters

Introduction and Consent for questionnaire survey

Greetings, My name is _____ do you live here? I am helping Anthonia Ijeoma Onyehialam in administering questionnaires for her PhD research work.

Mrs Anthonia Onyehialam is conducting a PhD student research on malaria disease and the social and physical environment. The questionnaire survey and observation protocol is being administered is to obtain information at household level on

- Malaria
- Working environments
- Housing characteristics
- Economic characteristics
- household characteristics
- physical and social access to health care usage

I will very much appreciate your participation in this survey. It takes 30 to 45 minutes and involves your response to a series of questions and the observation of your housing and environment characteristics and the measurement of its location. This information will support the achievement of a PhD that could also influence future malaria intervention policies. Whatever information you provide will be kept strictly confidential and will not be shown to other persons. Should you have any queries or concerns please feel free to contact her or academic supervisor in the following ways.

Anthonia Ijeoma Onyehialam Email: a.i.onyehialam@ncl.ac.uk

Telephone: +234-7086124580

Dr Eugene Sobngwi: eugene.sobngwi@ncl.ac.uk

I also like to let you know that participation in the survey is completely voluntary and targeted for respondents above 18 years of age. If this applies to you and we should come to any question you don't want to answer, please let me know and I will proceed to the next question. You can also stop the interview at anytime should you wish to. However, since your views are important, we hope you will participate in the survey.

At this time, do you want to ask me anything about the survey?

Sir/Ma are the head of the household? And are you above 18 years of age? (If yes continue otherwise ask for head/spouse/ someone above 18 years of age)

Head of household/spouse/other above 18 years (Signify)

Do you have a preference for written or verbal consent? **(Mark choice and where written preference is preferred signature of respondent required)**

- Written consent.....
- Verbal consent

May I let you know that as part of the incentive, at the end of the study you will receive a feedback report unless you state otherwise.

May I begin the interview now?

Thank you for your time. After each question, I will read out the answers and you can choose the most appropriate.

Give one copy of this information page to the respondent

Interviewer Instructions

Please circle appropriate answers given by participant and where open-ended questions are asked write down the answers as exactly presented by the respondent.

Do not use your own words.

START

Sir/Ma before we continue, we will like to send you a report at the end of the project. Would you be happy with that?

If yes, how would you like the report sent to you?

1. Email
2. Hand
3. Post
4. Other (specify)

Instructions: if yes reconfirm at end of survey and collect contact details

Thank you for your time, Sir/Ma I will begin with asking you some questions on malaria.

MALARIA

At what time of the year do you or household members experience malaria most frequently? (Pls pick the most suitable timelines that can be remembered by respondent)

1. New Year	
2. Christmas	
3. Easter	
4. Long vacation	
5. Others (specify)	

1. January	
2. February	
3. March	
4. April	
5. May	
6. June	
7. July	
8. August	
9. September	
10. October	
11. November	
12. December	

1. Dry season	
2. Wet season	

Does your family have mosquito net(s)?

1. Yes
2. No
3. Others (specify)

If yes, is it the insecticide treated mosquito net?

1. Yes
2. No
3. I don't know

How many mosquito nets do your household have whether treated or not?

.....

If yes, who sleeps under the mosquito net?

.....

Was the mosquito net used last night?

1. Yes
2. No
3. Others (specify)

Sir/Ma do you use any of the following for mosquito protection in the home?

	Yes	No
Window nets		
Door nets		

At the first instance, when malaria is suspected in your household what do you do?

	Y	N
1. Do nothing and wait to see if it gets more serious		
2. Buy medicine immediately at chemist/shop to take first		
3. Buy agbo or any herbal treatment to take first		
4. Go and conduct a lab test		
5. Go to the hospital		
Others (please specify)		

Have you or anyone in your household had malaria in the last year?

If yes, how was it treated?

What about malaria in the last month?

If yes, how was it treated?

Please indicate which of the ways I will mention you use to protect yourself and household members from having malaria?

	Y	N
1. Taking herbal remedies like agbo		
2. Insecticide treated mosquito net		
3. Door net		
4. Window net		
5. Mosquito coil		
6. Burning of cow dung		
7. Eating well		
8. Covering oneself when staying outside in the late evening or night		
9. Taking preventive medication		
10. Insecticide spraying		
11. Repellent gel		
12. Avoiding bushes, and vegetation around the living premises		
13. Cleaning drains and preventing stagnant water around		
14. Taking 7 up and salt		
15. Drinking alcohol		

Which of the following do you think cause malaria?

	Y	N
1. Mosquito bites		
2. touching a person with malaria		
3. staying under the sun, near heat or fire		
4. eating oily and fatty food		
5. Eating unripe or overripe fruits like pawpaw, mango		
6. Constipation		
7. Eating food touched by houseflies		
8. Through breast feeding a baby		
9. Drinking too much alcohol		

Sir/Ma I which of the following signs you think is associated with mild or severe malaria?

	Y	N	I don't know
1. Fever or continuous high fever and temperature			
2. Persistence headache			
3. Aches and Pain			
4. Loss of Appetite			
5. Dizziness			
6. Shivering			
7. Talking while sleeping			
8. Mouth bitterness			
9. Vomiting			
10. Cough			
11. Convulsion			
12. Anaemia			
13. Yellowness/Jaundice			

Which of the following factors influence the type of treatment you choose when there is malaria in your household?

	Y	N
1. Finance available at hand		
2. Seriousness of the malaria		
3. Husband/wife/parent (circle)		
4. Ability of sick person to describe symptoms accurately		
5. Age of sick person		
6. Nearness of hospital		
7. Extent of knowledge on how to treat malaria at home		
8. Time at which the illness started		
9. Place of occurrence of illness		
10. No thought is given to this as malaria is a simple illness that can be treated at home		

Which of the following risks do you and household members take?

	Y	N
1. Leaving doors or windows open for mosquitoes		
2. Relaxing outside in the evening without cover or protection from mosquitoes		

What job shifts do the following do, if you have a spouse and other household members. I will read out the responses and please let me know which one applies

	Your-self	Spouse (W/A)	Others
1. Day			
2. Night			
3. Both day and night			
4. Others (specify)			

Where in Lagos and beyond is the place of work of the following located?

Yourself	Spouse	Others

At the place of work where do you and members of your household work?

	Yourself	Spouse	Others
1. Outside the building			
2. Inside the building			
3. Both inside and outside the building			
4. Others (specify)			

Which of the following mosquito protection is used at the place of work of the following household members?

	Yourself	Spouse	Others
1. Window net			
2. Door net			
3. Mosquito spray			

How often per week do the following (where applicable) make journeys outside your immediate community including work, visit & social events?

	Yourself	Spouse	Others
1. Every day			
2. Six times/week			
3. Three times/week			
4. Twice/week			
5. Once/week			
6. Others (specify)			

Have you or any household member made an overnight journey to the outskirts of Lagos (I mean places like e.g Ikorodu, Epe, Badagry areas) in the last year?

1. Yes (Where?)
2. No

Have you or any household member make a journey outside of Lagos or any village in the last year?

1. Yes (Where?.....)
2. No

HOUSING CHARACTERISTICS

What type of accommodation do you live in with your household?

1. One room in flat /duplex /bungalow /storey building
2. self contained
3. flat
4. chalet
5. duplex
6. bungalow
7. storey building
8. shared facility (sharing toilet, bathroom, kitchen)

Sir/Ma which of the following are you to the accommodation?

1. Owner
2. Owner's representative/caretaker
3. Family ownership/living rent free
4. Renter/Tenant
5. Others (specify)

How long have you lived in this accommodation?

1. Less than one year
2. One to Three years
3. Four to Six years
4. Seven to nine years
5. Ten years and above

What materials are used for building walls?

1. No walls
2. Cement
3. Bricks
4. Mud/Earth/Laterite
5. Raffia leaves
6. Wood
7. Cardboard
8. Stone
9. Tarpaulin
10. Plastic cover
11. Others (specify)

What materials are used for the building roofs?

1. No roofs
2. Plastic
3. Corrugated metal sheets
4. Tiles
5. Long span aluminium
6. Zinc
7. Wood
8. Concrete slabs
9. Others (specify)

Sir/Ma how many rooms in total are in your household? **(Count bedrooms, and sitting/living room but exclude kitchen, bathroom and toilet if it is shared)**
.....

Sir/Ma how many bedrooms do you have in your accommodation?

How many rooms altogether are used for sleeping?

Please Sir/Ma how many of the following do you have in the accommodation?

Sleeping beds/frames		Mattresses/foams	Mats

What type of toilet facility do you and the household usually use?

1. Flush toilet
2. Pour flush toilet
3. Pit latrine
4. Composting toilet
5. No toilet facility/Bush/Field
6. Others (please specify)

Do you share the toilet facility with other households?

1. Yes
2. No
3. Others (specify)

If yes, how many households use this toilet facility?

Which of the water sources is in your household?

	Yes	No
Piped water into house		
Piped water to yard/compound		
Public tap		
Drawn well		
Purchased water		
Water from rivers, streams, canals, etc		
Others (specify)		

HOMESTEAD CHARACTERISTICS

Are there pets, livestock, household animals including pigs, goats, chicken, rabbit etc kept in the compound/yard even though they do not belong to you?

1. Yes
2. No
3. Others (specify)

Do you also store water in the house or within compound?

1. Yes
2. No
3. Others (specify)

ECONOMIC CHARACTERISTICS

Sir/Ma I will ask about equipments/assets ownership for establishing relationship between malaria and economic characteristics.

Which of the following cooking fuel do you use to cook?

	Y	N
Electricity		
Gas		
Kerosene		
Charcoal		
Coal		
Firewood		
Grass		
No food cooked		
Others (pls specify)		

Sir/Ma Please does any member of your household own any of the following items in good working condition?

	Y	N
Radio		
CD/DVD player		
Television		
Cassette player		
Bank account		
Sewing machine		
Deep Freezer		
Fan		
property/shares/land/investments		
Okada		
Car/Taxi/Van/Truck		
Generator		
Computer/laptop		
Electric Iron		
Cable TV e.g DsTV, HiTV etc		
Air conditioner		
Internet		
Canoe/ferry/boat with motor engine		
Paid domestic servant/house girl/boy		
Foreign vacation travel in the last 2 years		
Use of security guards and services		

What is your estimated income/earnings from salary, business, dash, etc., per day/week/month/year?

.....

If you estimate what your income has been in the last 10 years?

	Higher	Same	Lower
Was it lower or higher 3 years ago than presently?			
Was is lower or higher 6 years ago than presently?			
Was is lower or higher 9 years ago than presently?			
Was is lower or higher 10 years ago than presently?			

HEALTH CARE USE AND ACCESSIBILITY

Sir/Ma I will still like to ask you more about your use of health care facilities in treatment of malaria

Which of the following health care type do you or household members use for malaria treatment?

PUBLIC SECTOR	Y	N
Government-owned clinic / hospital		

OTHER SOURCE	Y	N
Church/Prophet/Pastor		
Mosque/Alfa		
Ala Agbo/Traditional healer		
Others (specify)		

PRIVATE MEDICAL SECTOR	Y	N
Private clinic or hospital		
Pharmacy		
Chemist/patent medicine store/shop		
Home visit by private doctor/nurse		
Nurse		
Other private (specify)		

How long do you wait for malaria to get serious before going to seek care at a health care facility for the following where applicable?

Pregnant woman	Child less than 5 years	Adult & others above 5 years

Which health care facility do you use? Please give name and location

.....

If you use a health care facility, in average how much does it cost to treat malaria? (This includes cost of drugs, tests, and consultancy charges)

Amount (Naira)	Private	Public	Others
Less than 300			
301 to 600			
601 to 900			
901 to 1200			
1201 to 1500			
1501 to 2000			
2001 and above			

For how long have you being using this health care?

	Private	Public	Others
Less than 2 years			
Above 2 years to 4 years			
Above 4 years to 6 years			
Greater than 6 years			

Where applicable what transport type do you normally use to visit the health care facility?

	Private	Public	Others
Walking			
Public transport			
Own vehicle			
Someone's vehicle			
Others (specify)			

For how long do you need to travel to reach the health care facility? Please mark relevant ones that are used

Time (Minutes)	Private	Public	Others
< 10 mins			
11 to 20 mins			
21 to 30 mins			
31 to 1 hour			
Home visit only			

If you use public transport, how many public transport means do you use to reach the health care facility?

No	Private	Public	Others
One			
Two			
Three			
Greater than three			

If you use personal transport how much in fuel or transport does it cost you to reach the health care facility where applicable?

Private	Public	Others

HOUSEHOLD AND DEMOGRAPHIC CHARACTERISTICS

Sir/Ma I will like to ask you some background and household questions in order for me to understand malaria experiences within the household.

What religions do you and household practise?

1. Christianity
2. Islam
3. Traditional Religion
4. No belief in God
5. Others (please specify)

Please approximately how old are you?

How many years altogether of completed education did you do? (Completed years only, please count from primary school until stopped)

What is your academic qualification?

1. None
2. Primary School Certificate
3. Junior Secondary School
4. SSCE/WASC/WAEC/GCE/NECO
5. Higher Education
6. Others (Please specify)

If you have a spouse, how many years of completed education does he/she have? (Completed years only, count from primary school until stopped)

Sir/Ma please, what is your marital status?

1. Single
2. Married
3. Divorced
4. Living together in a relationship but not married
5. Widowed
6. Others (please specify)

Please indicate your gender

1. Male
2. Female
3. Others (please specify)

And please what is your native language?

1. Hausa
2. Yoruba
3. Igbo
4. Others (please specify)

.....

Sir/Ma can you please tell me how many people fall in this age range in your household? (This means a person or group of persons living in same residence and eating from same pot)

1. 0 to 4 years
2. 5 to 14 years
3. 15 to 19 years
4. 20 to 49 years
5. 50 years and above

Have you got any traveller from abroad staying with you?

- a) Yes
- b) No
- c) I don't know

Do you have any pregnant member of the household?

- d) Yes
- e) No
- f) I don't know

What were you originally trained to do for a living?

What type of job do you presently do?

.....

If applicable, in a couple who has the greatest say in deciding what malaria treatment will be taken

1. Husband
2. Wife
3. Both equally
4. Don't know, depends

CONCLUSION

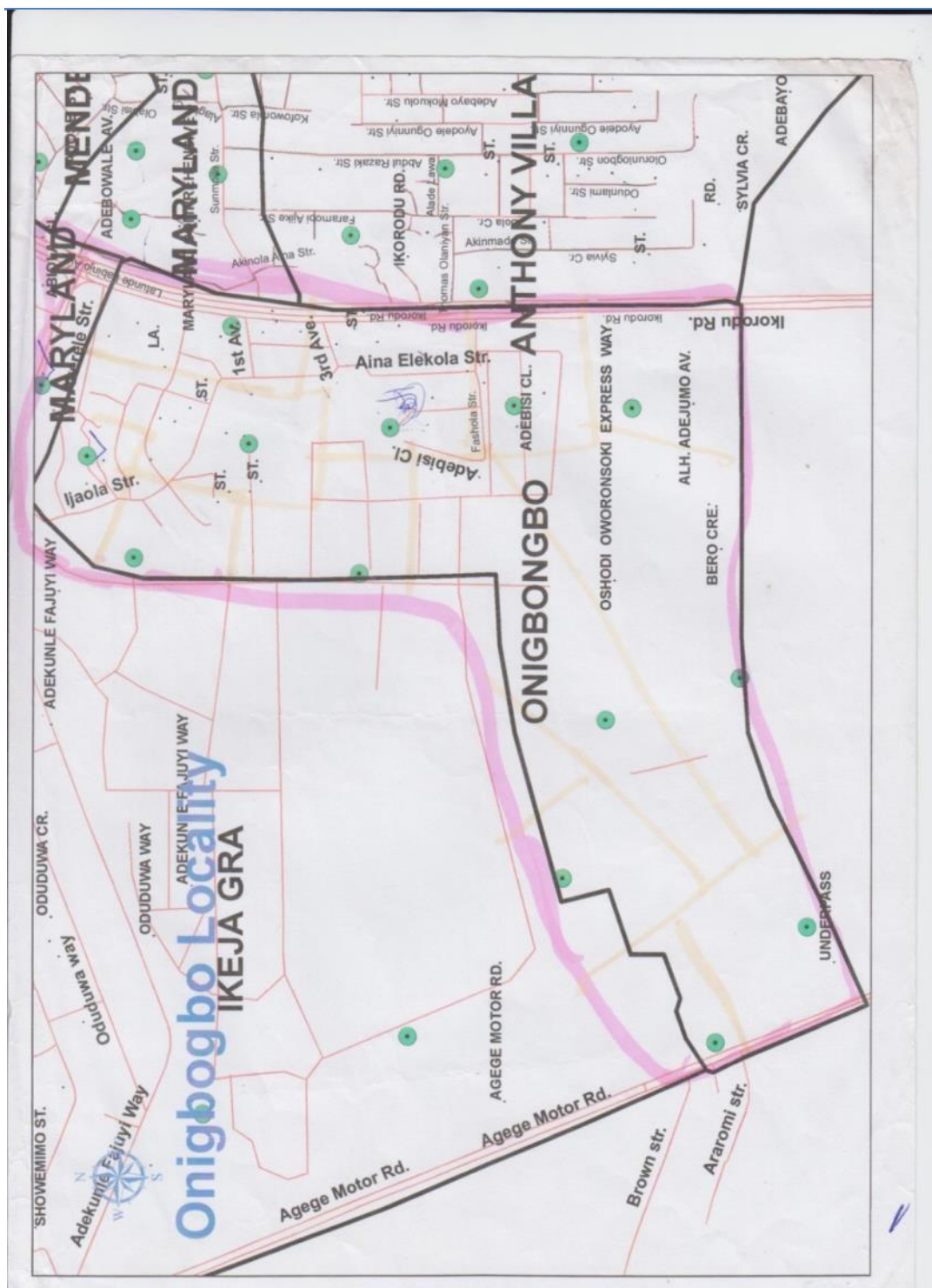
Thank you for your time.

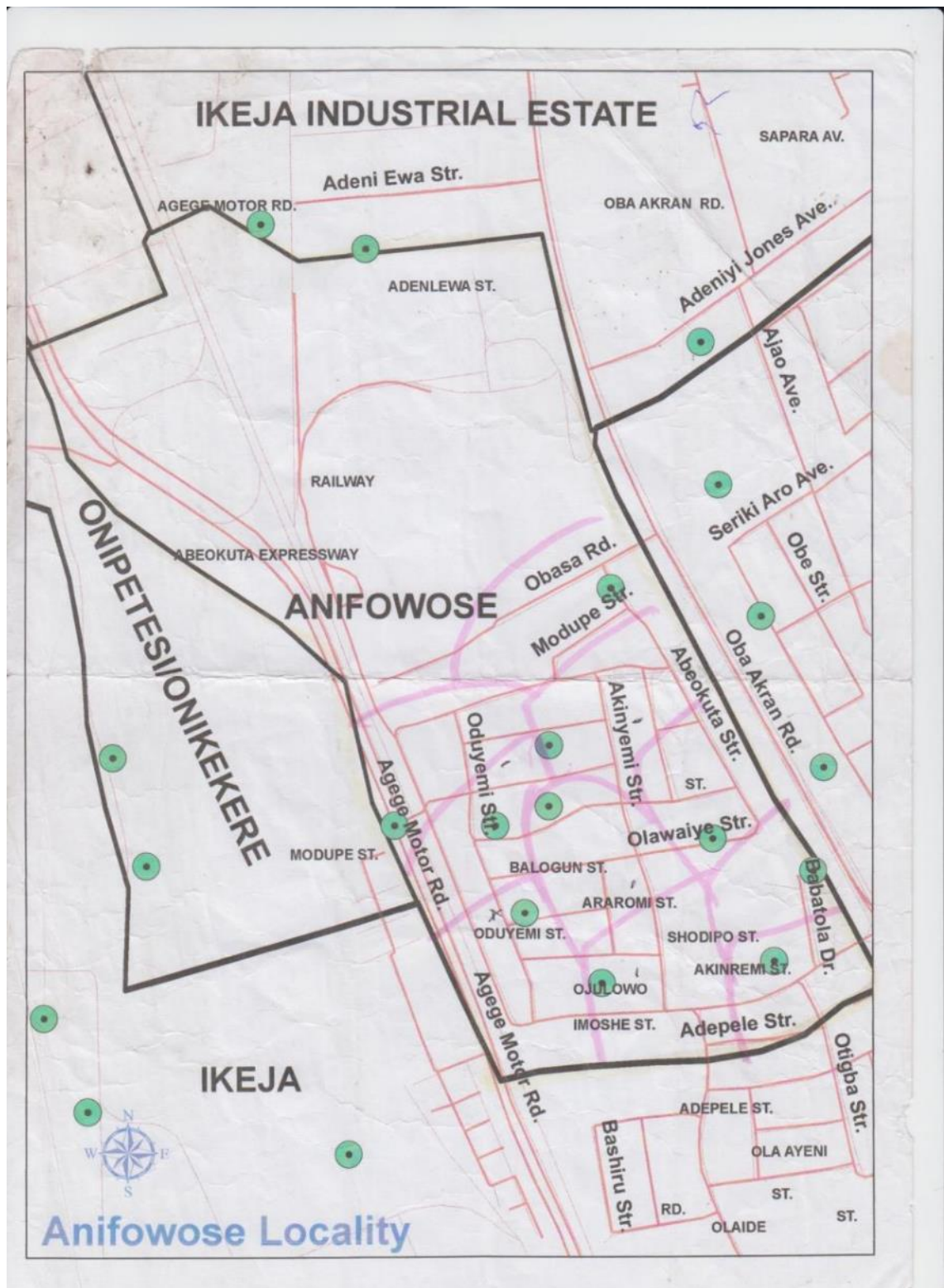
Please can I please have your contact details for further correspondence?

.....

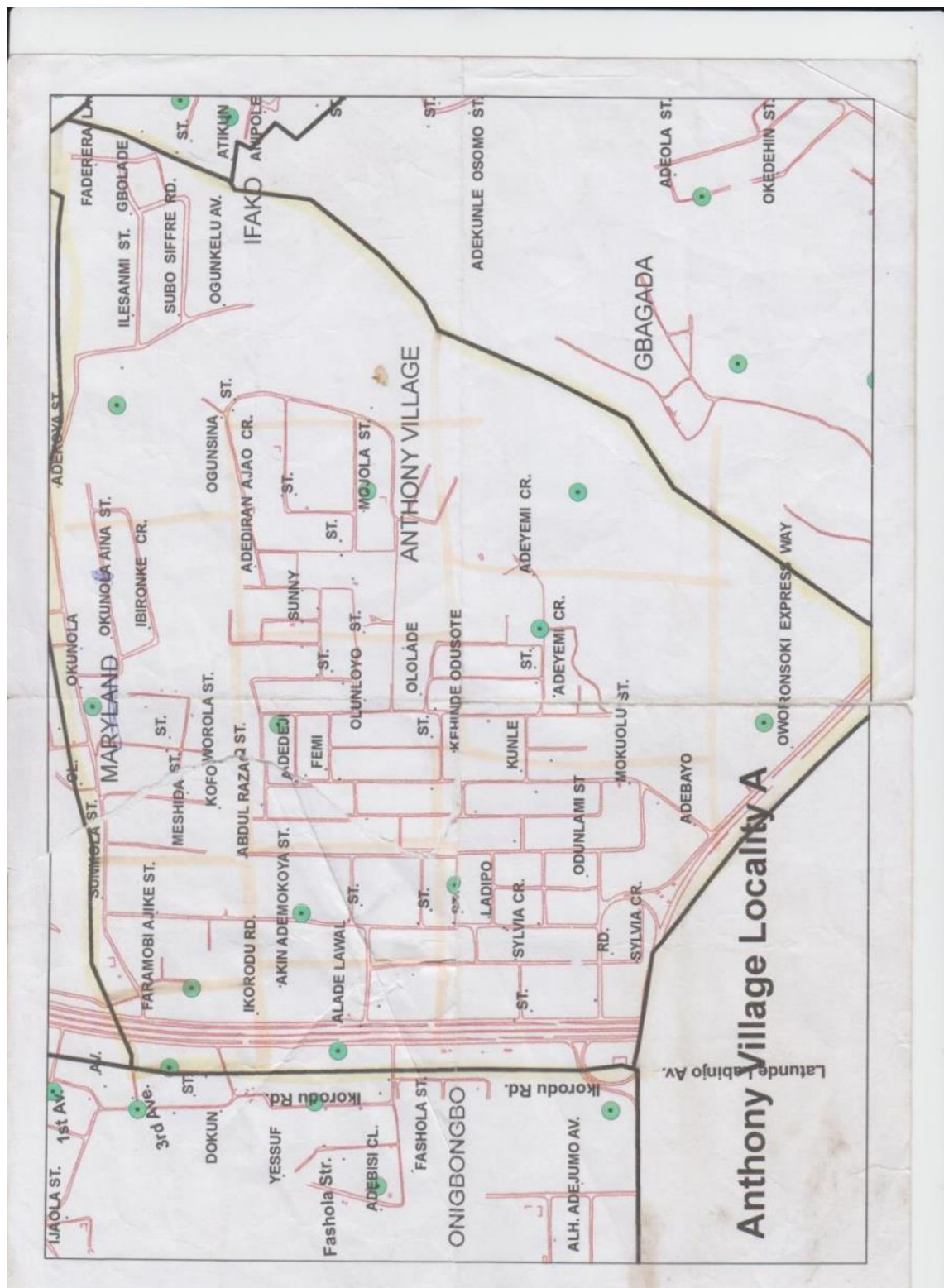
Thank you Sir/Ma for your time and support, it is very much appreciated.

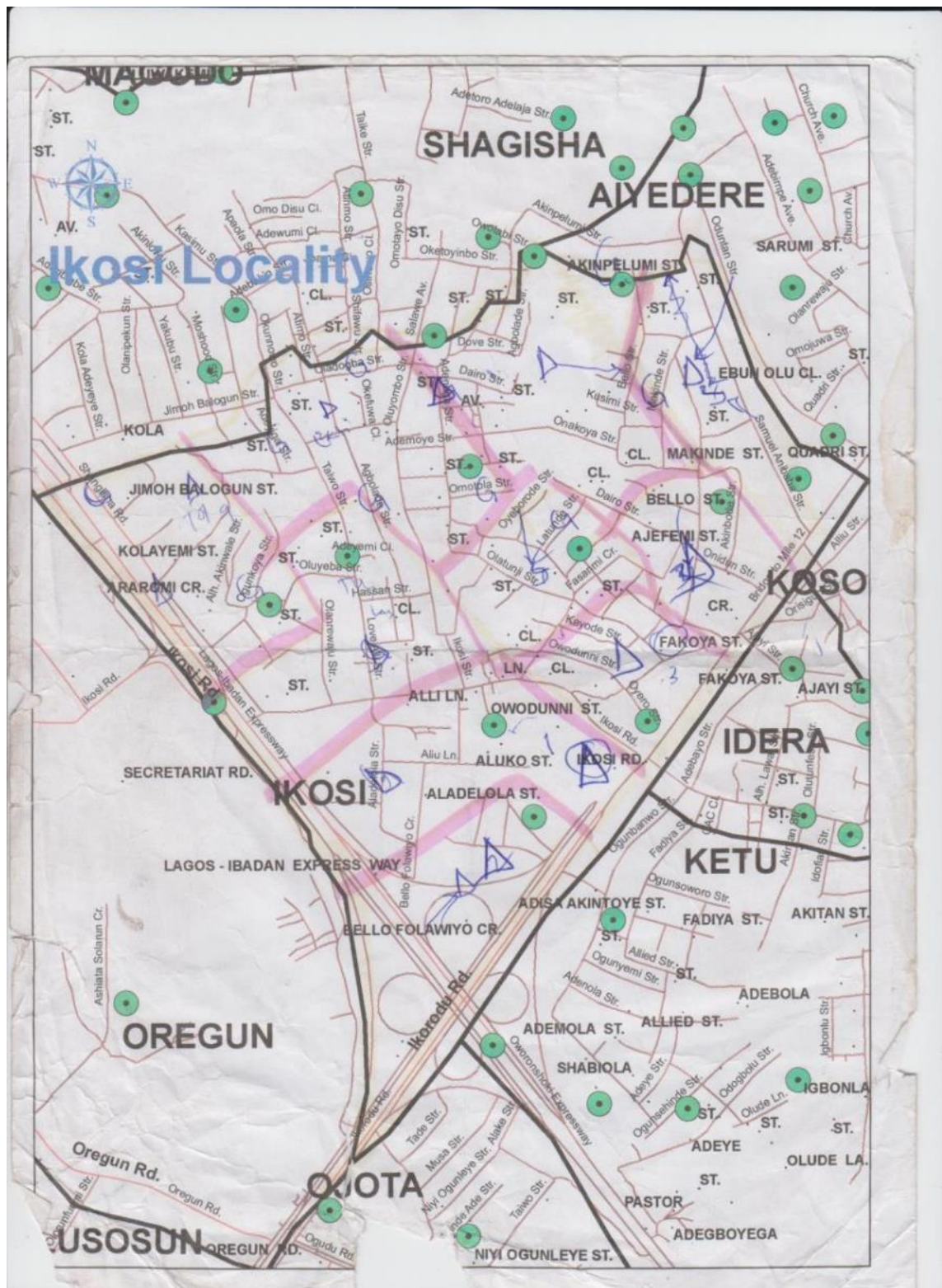
Appendix XIX: Map Sampling Framework





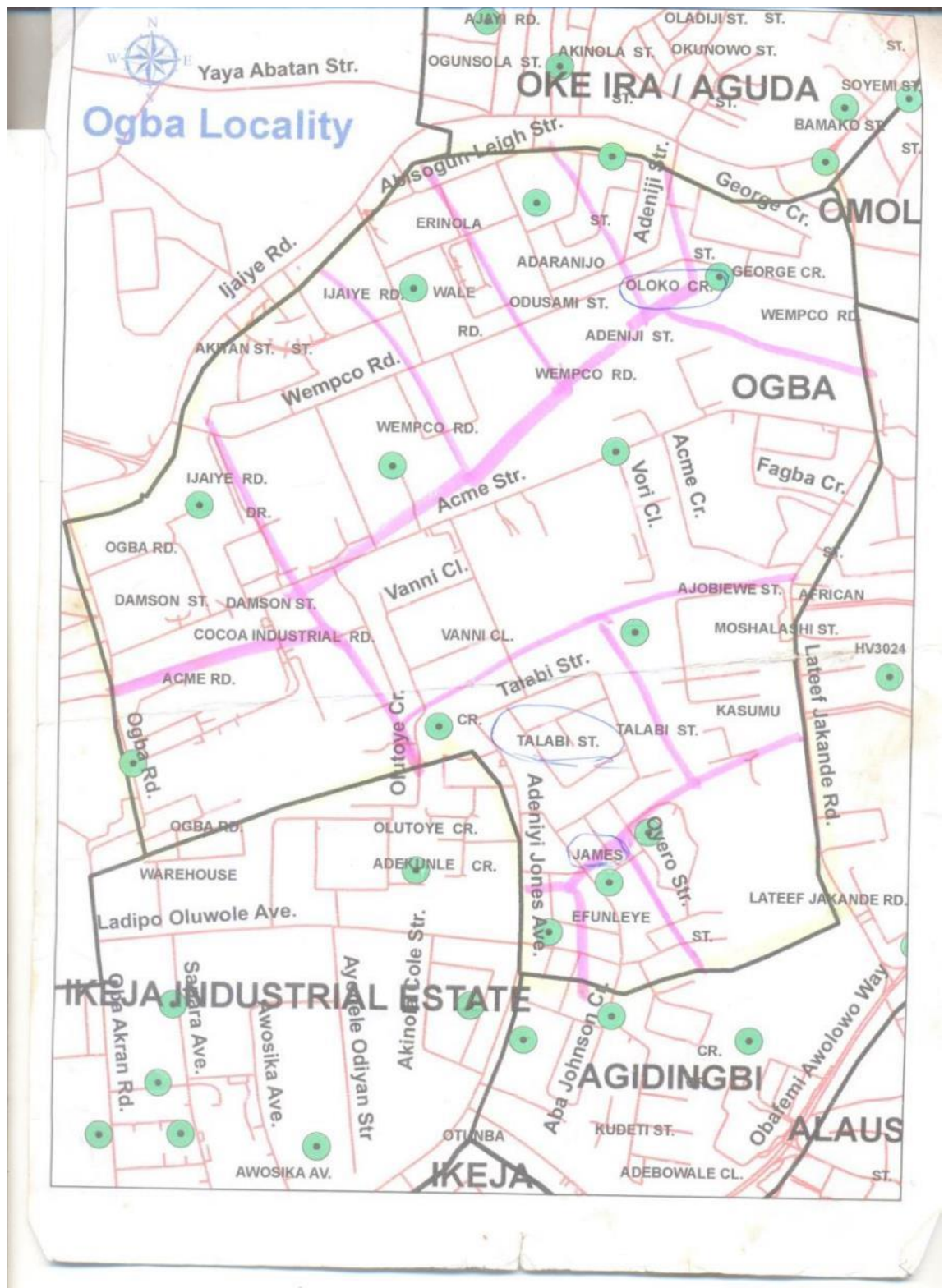


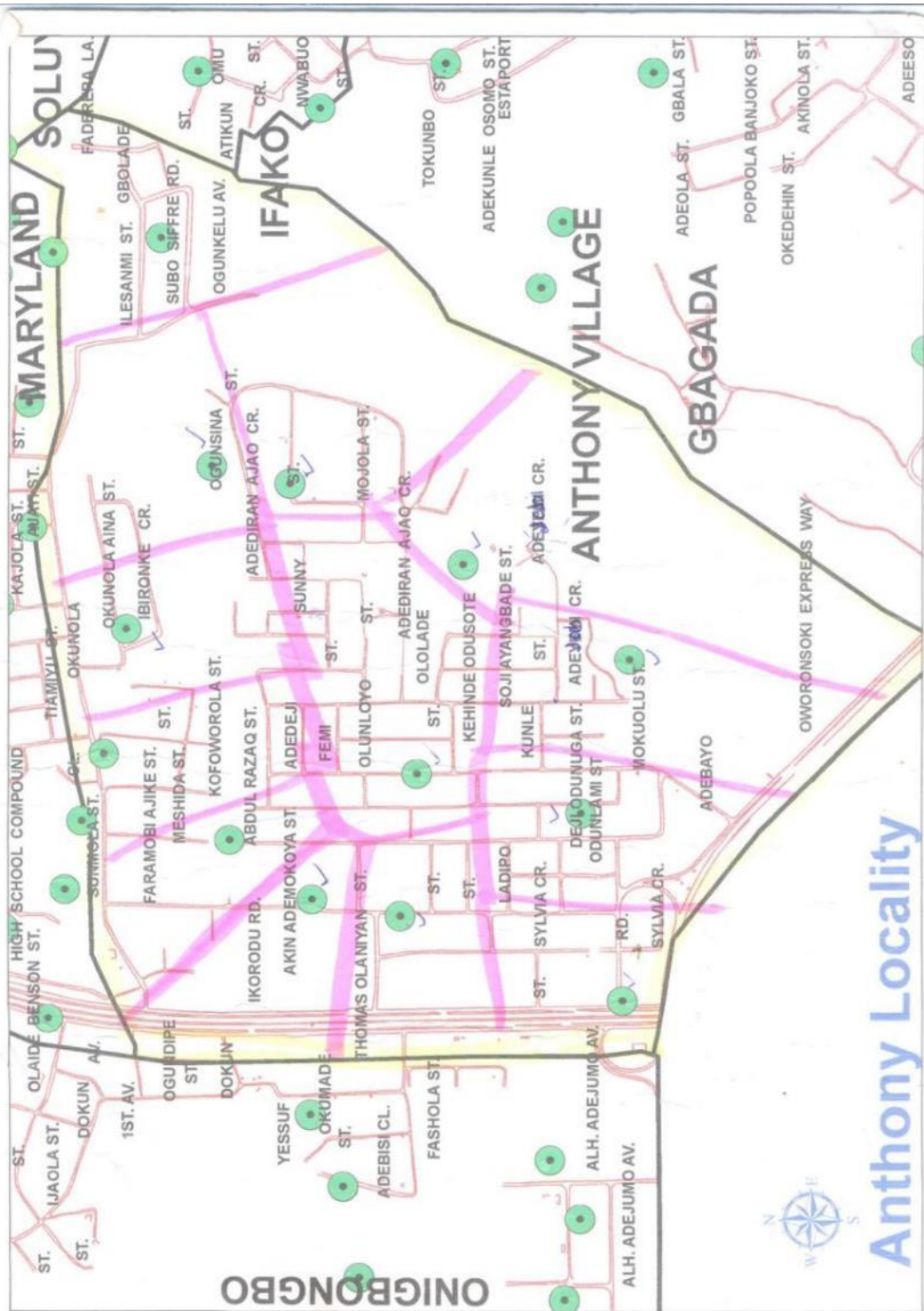


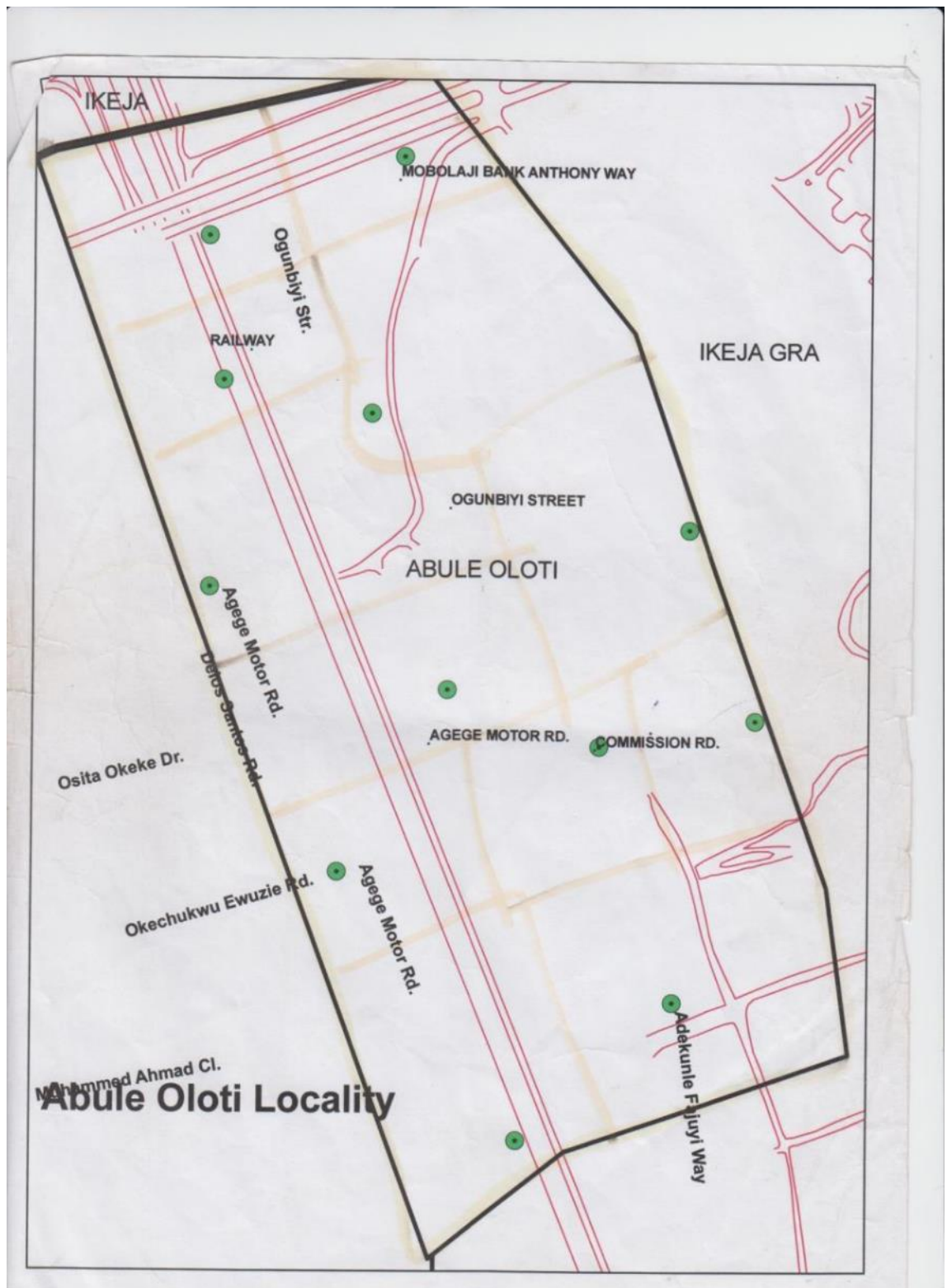


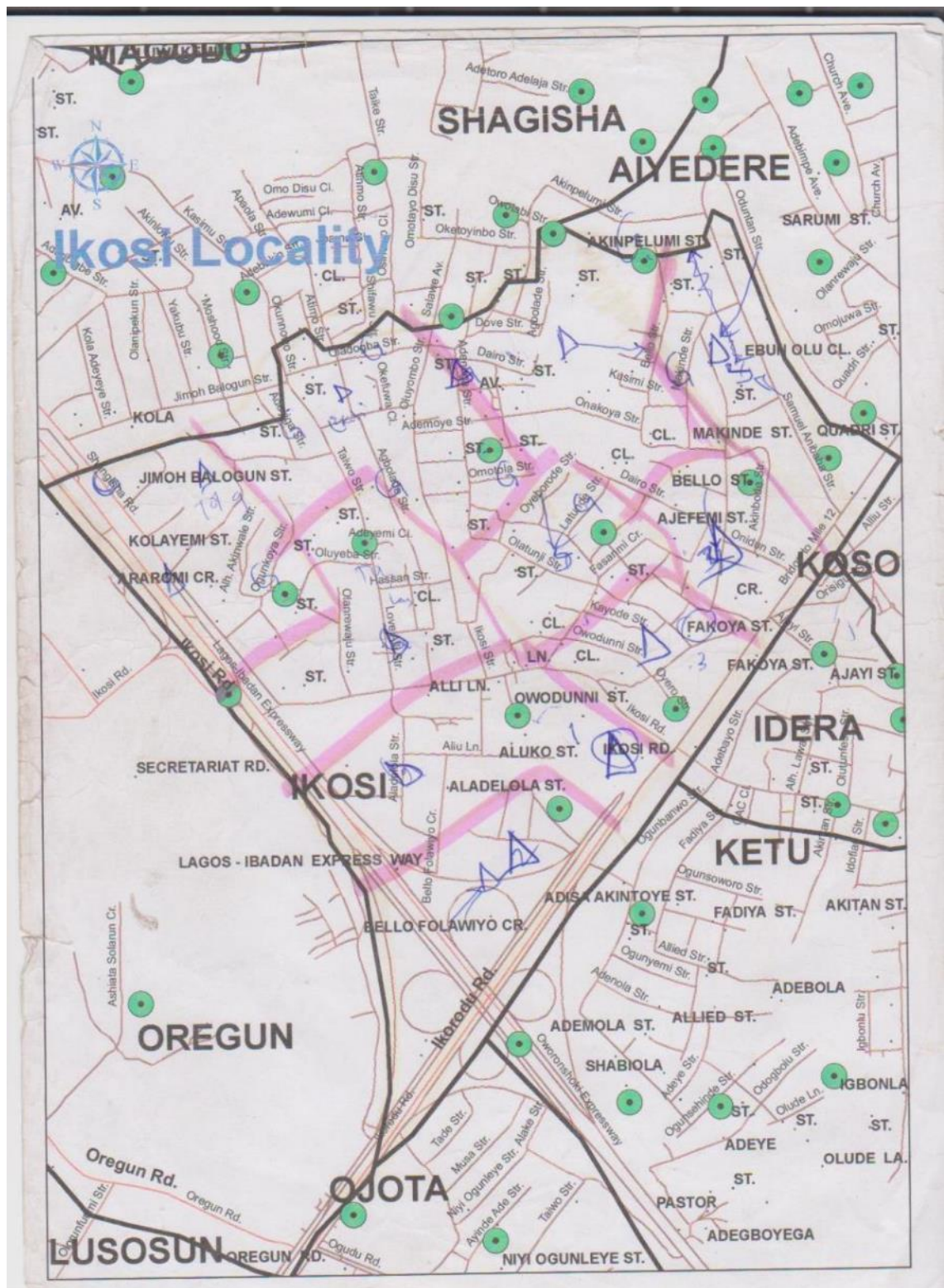












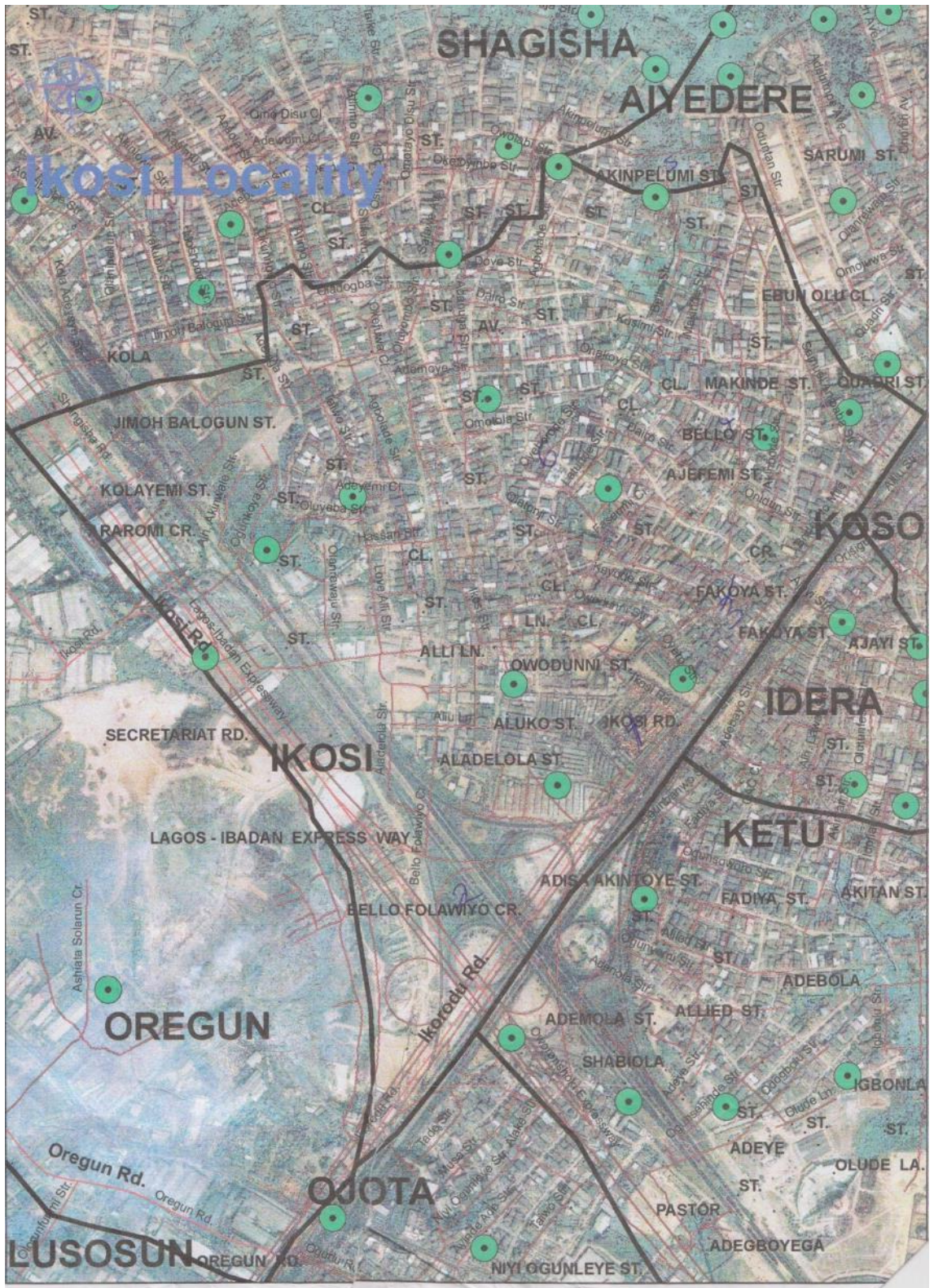
Appendix XX: Imagery Maps of Localities





















Appendix XXI: Sample List of Supervisory and Enumeration Areas (EAs)

Supervisory Areas		EAs	
785	Balogun/Lawe Str	1782	Oluwatoyin/Balogun Lane Ketu
795	Bola Owodunni	1784	Oluwakemi/Bola Owoduuni Alapere
795	Bola Owodunni	1786	Seriki/Bola Owodunni/Ajibola Alapere
805	Unity Avenue	1788	Agboyi Rd/Ogunjobi Oniwu Ketu
805	Unity Avenue	1790	Agboyi Rd Ketu
805	Unity Avenue	1792	Agboyi /AlhSalami Str Ketu
805	Unity Avenue	1794	Alh Salami/Ojaomo Str Ketu
675	Agbayi Road	1796	Agbayi Road Ketu
820	Okeowo Close	1798	Okeowo Close/Oyemomi Ketu
820	Okeowo Close	1800	Rev. Kwakpouine Str Ketu
820	Okeowo Close	1802	Alh Shittu Imewabu Ketu
820	Okeowo Close	1804	Oyemomi/Igbolo Str Ketu
810	Emmanuel	1808	Ajibola /Ifeoluwa Str Ketu
810	Emmanuel	1810	Emmanuel/Alausa/ajibola Ketu
810	Emmanuel	1812	Emmanuel/Emiyanu/Olalowo Ketu
795	Bola Owodunni	1814	Tinubu Street Alapere
795	Bola Owodunni	1816	Olusanya/Bola Owodunni Alapere
795	Bola Owodunni	1818	Adeptan /Olusanya Alapere
785	Balogun/Lawe Str	1820	Balogun /Lawe/Anuoluwapo Ketu
780	Alapere Est (Exp)	1822	Balogun Ilawe /Anuoluwapo Alapere
790	Solomon Street	1824	Anuoluswapo /Adeptan Ketu
790	Solomon Street	1826	Abimbola /Solomon str Ketu
780	Alapere Est (Exp)	1828	Alapere Est (Exp) Ketu
790	Solomon Street	1830	Adeola Solomon /Adegbesan Ketu
790	Solomon Street	1832	Bola Hassan/Adeptan Ketu
790	Solomon Street	1834	Balogun Kuku Str Ketu
790	Solomon Street	1836	Ezobi/Lagbake Str Ketu
800	Balogun Kuku	1838	Ezobi/Balogun Kuku Alapere
800	Balogun Kuku	1840	Ezobi/Adeptan Close Alapere
800	Balogun Kuku	1842	Irepodun/Afolabi Alapere
810	Emmanuel	1844	Adisa Balogun/Lambo Str Ketu
810	Emmanuel	1846	Lambo/Adisa Bal. / Akinyemi Ketu
810	Emmanuel	1848	Igboho Str Ketu
830	The Anglican Church	1854	Omotayo/ Ayo Buhari Str. Ketu
830	The Anglican Church	1856	The Anglican Church Ketu
830	The Anglican Church	1858	Bola Adegboro/ Igbowo Good Ketu
805	Unity Avenue	1860	Unity Ave/Ajibola Crescent Ketu
800	Balogun Kuku	1862	Unity/Majekodunmi/Ijola Alapere
800	Balogun Kuku	1864	Afolabi/Majekodunmi/Lambo Alapere
815	Mobile Police Barrack	1866	Mobile Police Barrack Ketu
815	Mobile Police Barrack	1868	Moral Int Sch Ketu
830	The Anglican Church	1870	Nimbus Medical Centre Ketu
830	The Anglican Church	1872	Chapel of Liberty Ketu
815	Mobile Police Barrack	1874	Septre Int Sch Ketu
815	Mobile Police Barrack	1876	Oketunde Church Ketu
815	Mobile Police Barrack	1878	Soulmate Hotel Ketu
820	Okeowo Close	1880	Adisa Balogun /Unity Ave Ketu
780	Alapere Est (Exp)	1882	Debo Adebayo Lane ogudu
780	Alapere Est (Exp)	1884	Adebola /Alh Eleshin ogudu
380	17 Shonaike Str	1886	Shinaike Str/Aladeola Ikosi
380	17 Shonaike Str	1888	17 Shonaike Str Ikosi
380	17 Shonaike Str	1890	6 Abeni Close/Jmoh Balogun Ikosi
[REDACTED]		[REDACTED]	
[REDACTED]		[REDACTED]	
[REDACTED]		[REDACTED]	
[REDACTED]		[REDACTED]	
[REDACTED]		[REDACTED]	

Appendix XXII: Projects by Lagos State Government That are Taking up Personal Lands



Oshodi Heritage Garden, Oshodi, Lagos. Source: www.informationng.com



Bus Rapid Transit Park in Kosofe, Lagos. Source: nigeriavillagesquare.com

Accessed November 2012



Former homes of participants of household survey now taken over (post fieldwork) by government for project development



Former homes of participants of household survey now taken over (post fieldwork) by government for project development

Appendix XXIII: Follow-up on Non-response Questionnaires

To call back 1KJ Not cooperative F04

Anthonia Ijeoma Onyiahialam PhD Research Candidate Geography, Politics and Sociology Telephone: 07086124580	Confidential Questionnaire for Academic Research Purposes
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Objectives of Questionnaire

1. To obtain socio economic information at household level on
 1. income
 2. literacy level
 3. physical and social access to health care
 4. living conditions
 5. working conditions
 6. occupation
 7. migrational patterns
 8. cultural ways that exposes oneself to malaria
2. To obtain information on their KAP to malaria
3. To interview people at their household residence

3rd Not cooperative Follow up ended November 2010

Interviewer Details	Respondent Details
Questionnaire No: 2010/AIO/PHM/Main F0001	House Address: [REDACTED]
Name of Interviewer: [REDACTED]	GPS Coordinate [REDACTED] F0001
Telephone number [REDACTED]	Type of Building: Duplex
Date of Interview: 24/07/2010	Name of locality: Harris Avenue Avenue Agidingbo

Interviewer Instructions

1. Please all questionnaires must be administered at the place of residence of respondents. Do not interview people at their place of work.
2. Take GPS coordinates of the residences after questionnaire has been administered and not before
3. Please keep safe, avoid as much as possible entering into people's houses. Especially ladies.

Dec 2010. 3rd attempt

claimed wrong number

no answer

Not available

F071

Anthonia Ijeoma Onyiahialam PhD Research Candidate Geography, Politics and Sociology Telephone: 07086124580	Confidential Questionnaire for Academic Research Purposes
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Objectives of Questionnaire

1. To obtain socio economic information at household level on
 1. income
 2. literacy level
 3. physical and social access to health care
 4. living conditions
 5. working conditions
 6. occupation
 7. migrational patterns
 8. cultural ways that exposes oneself to malaria
2. To obtain information on their KAP to malaria
3. To interview people at their household residence

Interviewer Details	Respondent Details
Questionnaire No: 2010/AIO/PhD/Main F0010	House Address: [REDACTED]
Name of Interviewer: [REDACTED]	GPS Coordinate [REDACTED]
Telephone number [REDACTED]	Type of Building: 2-storey building/facade
Date of Interview: 25/7/2010	Name of Locality: Ikesi locality

Interviewer Instructions

1. Please all questionnaires must be administered at the place of residence of respondents. Do not interview people at their place of work.
2. Take GPS coordinates of the residences after questionnaire has been administered and not before
3. Please keep safe, avoid as much as possible entering into people's houses. Especially ladies.

Appendix XXIV: Difficulties with following up on Non-response Questionnaires



Source: eternalfilez.blogspot.com Accessed October 2010

Appendix XXV: AIC and AICc Estimation for Ten Candidate Predictive Models

<i>Candidate Model Number</i>	<i>2LL</i>	<i>sample size (n)</i>	<i>no of IRVs (k)</i>	<i>2k</i>	<i>AIC</i>	<i>k+1</i>	<i>2k (k+1)</i>	<i>n-k-1</i>	<i>2k(k+1)/n-k-1</i>	<i>AICc</i>
Candidate Predictive Model One (p-value ≤ 0.05 in a univariate logistic regression analysis)	234.984	208	4	8	242.984	5	40	203	0.197	243.181
Candidate Predictive Model Two (IRVs with p-values ≤ 0.25)	212.219	208	11	22	234.219	12	264	196	1.347	235.566
Candidate Predictive Model Three (Behavioural/Socio-Cultural Environmental IRVs)	225.935	208	11	22	247.935	12	264	196	1.347	249.282
Candidate Predictive Model Four (with Physical Environmental IRVs)	243.088	208	5	10	253.088	6	60	202	0.297	253.385
Candidate Predictive Model Five (Built Environmental IRVs)	241.165	208	10	20	261.165	11	220	197	1.117	262.282
Candidate Predictive Model Six (Physical and Built Environmental IRVs)	222.106	208	15	30	252.106	16	480	192	2.5	254.606
Candidate Predictive Model Seven (with theoretically relevant IRVs of the HED Framework)	192.480	208	26	52	244.48	27	1404	181	7.757	252.237
Candidate Predictive Model Eight (socio-cultural and physical environment)	214.668	208	16	32	246.668	17	544	191	2.848	249.516
Candidate Predictive Model Nine (socio-cultural and built environment)	210.379	208	21	42	252.379	22	924	186	4.968	257.347
Candidate Predictive Model Ten (with Statistically Significant Variables and Interaction Terms)	214.529	208	10	20	234.529	11	220	197	1.117	235.646

Appendix XXVI: Translations of Direct Quotes from Participants from Pidgin English to English

Translation 1:

..... My oga talk say I must sleep under net as they being dey talk for radio and health centre for people wey get belle.....

Translated:

My husband insists I should sleep under the mosquito net since the radio and the hospital recommend it for the good health of the mother and child.....

Translation 2:

Agbo get power well well, something wey dey kill witchcraft and ogbanje wey dey den send person wey get belle na malaria e go leave? ... Aaah e get power.

Translated:

Malaria is a small disease for agbo to treat; it is so powerful a remedy that it can eliminate the highest form of disease, witchcraft or bad spirits ... (demonstrates strength with his fists).

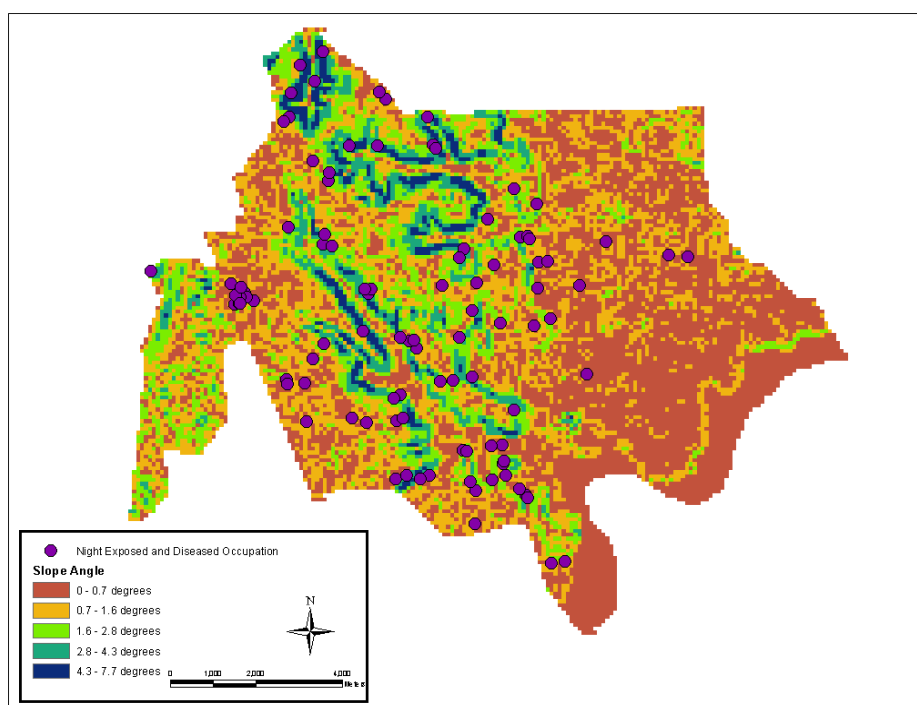
Translation 3:

When we come this place, we no get bed and I get belly. My oga talk say I must sleep under net as they being dey talk for radio and health centre for people wey get belle ... Dey give me net for ante natal so na so I dey sleep for chair take the net hang on top. When I born, my oga say I must continue because of the pickin until im get money buy bed. Na so I continue carry my pickin for hand. Money never come for bed and the thing come dey too much, when this kind thing go stop? I carry my baby put for my side lie down for ground make the pickin wey God give me no fall from my hand. I tell oga say nothing go do us. Na for ground I dey sleep since and I no fit use the net for ground. ... My oga bring net for window and door last week im oga commot im own and my oga take am for put for house ... I no know whether im dey work sah, in short I no know whether anything dey work.

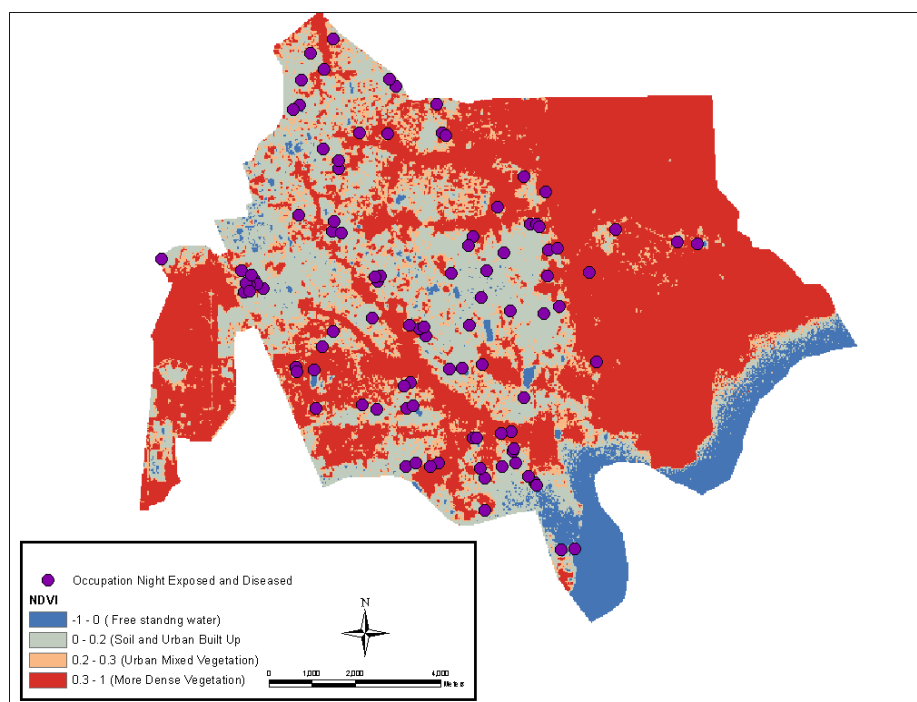
Translated:

When we moved to this accommodation, we didn't have any bed and I was pregnant. My husband insisted that I would sleep under the mosquito net I was given at the clinic since the radio and the hospital recommend it for the good health of the mother and child. Since we didn't have a bed, I used to sleep on the chair and hang the mosquito net over me. When the child was born, my husband insisted I had to continue to sleep under the net with the baby even though it was on a chair and so uncomfortable. I continued to sleep on the chair carrying my baby on my hands sometimes. The bed was not forthcoming and one day, I moved to the floor and made it my bed. I couldn't bear it anymore. I was so troubled that the baby that God has given me would fall out of my hand all because I wanted to be under a mosquito net which I couldn't find how to fit it because we didn't have a bed and we slept on the floor. I told my husband that nothing would happen to us if we slept on the floor without the mosquito net. I have been sleeping on the floor since then with my baby, we cannot fit the net on the floor ... My husband was given door and window nets that his boss removed from his house when he was replacing his screens. He just fixed them on our windows and doors ... I don't know if the window and door nets help to reduce malaria or mosquitoes, in fact I don't know if anything works including the ITNs. I don't know.

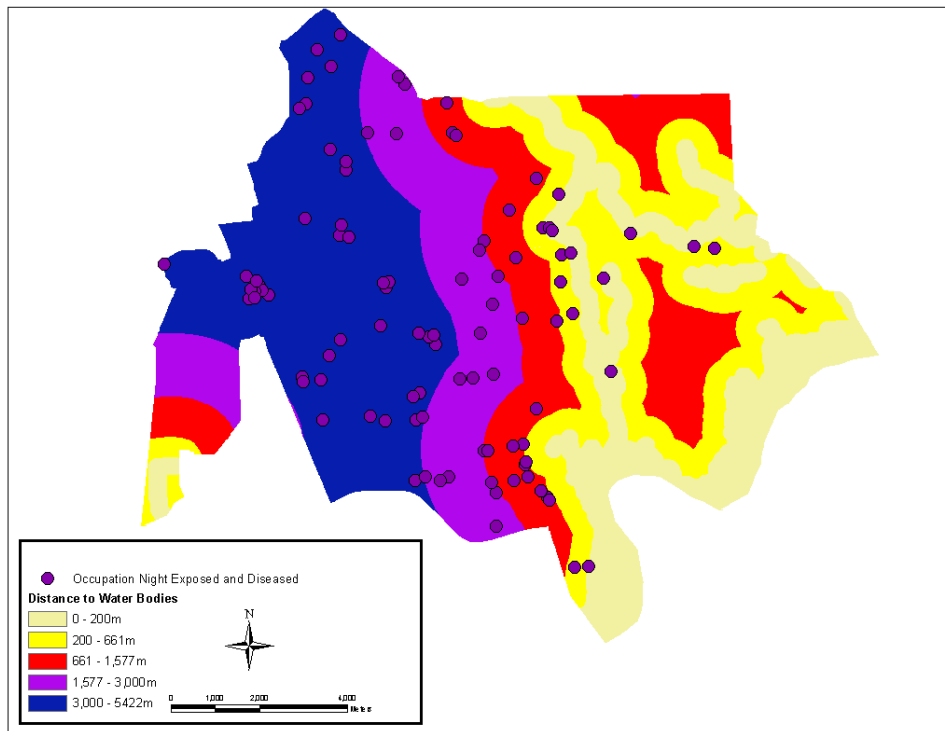
Appendix XXVII: Working at Night without Mosquito Protection overlaid on Physical Environmental Variables



Slope



NDVI



Distance to Water Bodies

Appendix XXVIII: Typical Scenario of Working at Night in Ikeja and Kosofe LGAs

